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DeepPhasePick: a method for detecting and picking seismic phases from local earthquakes based on highly optimized convolutional and recurrent deep neural networks

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SUMMARY

Seismic phase detection, identification and first-onset picking are basic but essential routines to analyse earthquake data. As both the number of seismic stations, globally and regionally, and the number of experiments greatly increase due to ever greater availability of instrumentation, automated data processing becomes more and more essential. For example for modern seismic experiments involving 100s to even 1000s instruments, conventional human analyst-based identification and picking of seismic phases is becoming unfeasible, and the introduction of automatic algorithms mandatory. In this paper, we introduce DeepPhasePick, an automatic two-stage method that detects and picks *P* and *S* seismic phases from local earthquakes. The method is entirely based on highly optimized deep neural networks, consisting of a first stage that detects the phases using a convolutional neural network, and a second stage that uses two recurrent neural networks to pick both phases. Detection is performed on three-component seismograms. *P*- and *S*-picking is then conducted on the vertical and the two-horizontal components, respectively. Systematic hyperparameter optimization was applied to select the best model architectures and to define both the filter applied to pre-process the seismic data as well as the characteristics of the window sample used to feed the models. We trained DeepPhasePick using seismic records extracted from two sets of manually picked event waveforms originating from northern Chile (~39 000 records for detection and ~36 000 records for picking). In different tectonic regimes, DeepPhasePick demonstrated the ability to both detect *P* and *S* phases from local earthquakes with high accuracy, as well as predict *P*- and *S*-phase time onsets with an analyst level of precision. DeepPhasePick additionally computes onset uncertainties based on the Monte Carlo Dropout technique as an approximation of Bayesian inference. This information can then further feed an associator algorithm in an earthquake location procedure.

Key words: South America; Neural networks, fuzzy logic; Time-series analysis; Body waves; Computational seismology.

1 INTRODUCTION

One of the most fundamental components in any earthquake hypocentre estimation routine is the identification and picking of the arriving *P* and *S* seismic phases. The identification of the *S*-phase arrivals is especially important, since this helps to better constrain hypocentre depths obtained only from *P*-phase arrivals. In the past, the phase picking task was commonly performed manually by analysts, who identified each phase arrival based on their training and experience. However, as the available seismic data has rapidly increased over time, the use of automatic phase detection algorithms has become increasingly necessary.

These automatic algorithms encompass detectors which are based on the energy or frequency content of the seismic waveforms such as STA/LTA (e.g. Allen 1978; Baer & Kradolfer 1987; Earle & Shearer 1994; Sleeman & van Eck 1999; Aldersons 2004; Di Stefano *et al.* 2006; Diehl *et al.* 2009), those based on correlations of template waveforms against continuous seismic data (e.g. Van Trees 1968; Harris 1991; Gibbons & Ringdal 2006), and detectors based on the representation of seismic data as a linear combination of orthogonal basis waveforms (Scharf & Friedlander 1994; Harris 1997, 2001).

Phase detectors based on frequency or energy have been used in the past as part of multistage automatic earthquake location procedures that allowed the creation of high-quality earthquake

Figure 1. Events data sets from which window samples picked by analysts were extracted for training the phase detection and picking models in DeepPhasePick. Events in S1 and S2 data sets are plotted as green and red circles, respectively. Focal mechanisms (beachballs) and epicentres (stars) of the 1995-07-30 $M8.1$ Antofagasta and the 2007-11-14 $M7.7$ Tocopilla earthquakes are plotted in green and red, for reference. Window samples used in this work come from the picked stations plotted as black triangles (from S1) and squares (from S2).

catalogues, for example for the Northern Chile region (Sippl *et al.* 2018; Soto *et al.* 2019). Correlation detectors, such as the matched filter method (Van Trees 1968), rely on the similarity of known template waveforms and have been widely used for detecting repeating earthquakes (e.g. Nadeau & Johnson 1998; Igarashi *et al.* 2003; Kato & Igarashi 2012; Huang *et al.* 2017; Folesky *et al.* 2018) or searching for missing events (e.g. Shelly *et al.* 2007; Peng & Zhao 2009; Ross *et al.* 2019a) in different tectonic regimes. Subspace detectors, which are based on orthogonal basis waveforms, have been used for identifying earthquakes associated to aftershock sequences and low-frequency tremors (Maceira *et al.* 2010; Harris & Dodge 2011).

Despite the fact that energy-based phase detectors do not require strong prior waveform knowledge, an increase in their ability to detect small onsets also implies higher false positive rates. Correlation detectors can achieve very low false positive rates, but they can solely detect similar signals to the ones already present in the

selected template waveforms (Harris 1991). Subspace detectors can further extend the range of detected signals, depending on which detection threshold and subspace dimension parameters are used (see e.g. Harris & Paik 2006). However, both correlation and subspace detectors are not easy to implement efficiently and hard to scale to very large data sets since they require a high computational cost.

All the above described methods exploit *a priori* assumed attributes of the signals such as energy or waveform similarity. Instead, deep learning methods learn signal characteristics directly from input data by applying non-linear transformations sequentially. In the supervised version of deep learning, the goal is to reduce the calculated error (objective function) between the network predictions and the known labels that the network is fed with (LeCun *et al.* 2015; Goodfellow *et al.* 2016). This is achieved by adjusting the connection weights between units in each layer after backpropagating the gradients of the objective function, computed over the

Figure 2. Seismic window extraction. (a) Example of an event waveform, outlining how the seismic window of three classes (N, P, S) are extracted for the optimized training of the phase detection model. N-, P- and S-class windows are extracted, respectively, in the vicinity of the event origin time (ot), and the true P- (tp) and S- (ts) onset times found by analysts. The hyperparameter win_size [s] defines the length of the extracted windows, which is equal for the three classes. (b) Zoom into the three-class windows. The starting time of the window before ot , tp and ts is defined by the hyperparameters $frac_pre_N$, $frac_pre_P$ and $frac_pre_S$ for classes N, P and S, respectively. Here $win_pre_C = win_size \times frac_pre_C$, where $C = N, P$ or S .

units in the last layer, to the input layer of the network. The network training consists of repeating the whole process for a fixed number of times (epochs) or until there is no further decrease in error (early stopping).

Convolutional neural networks (CNNs) are a class of deep neural networks specialized for processing unstructured data (Goodfellow *et al.* 2016). CNNs stand out due to the fact that they are computationally more efficient, easier to train, and have proven to effectively generalize learned features in many supervised tasks, ranging from image and document recognition (LeCun *et al.* 1990, 1998; Simard *et al.* 2003; Krizhevsky *et al.* 2012; Taigman *et al.* 2014) to seismic waves simulation (Moseley *et al.* 2018), or volcanic ash particles classification (Shoji *et al.* 2018).

Originally inspired by the properties observed in the primary visual cortex (PVC) of the mammalian brains (Hubel & Wiesel 1959, 1962), modern CNN architectures are usually formed by several stages of consecutive operations of convolution, non-linear transformation, pooling, and regularization. In the first stage, a filter (kernel) performs local weighted sums (convolutions) through the input data. This linearly activates or detects local features, emulating the behavior observed in the so-called simple cells of the PVC. The resulting feature maps are transformed by applying a non-linear function. A further function then summarizes its statistics in a local scale (pooling). Usually the maximum (max pooling) within a subregion is computed in this second function, inspired by the function of PVC complex cells (LeCun *et al.* 2015; Goodfellow *et al.* 2016). Convolution is highly efficient and effective because it takes advantage of the local connectivity and invariance to location exhibited by meaningful learnable features in natural signals. First, it detects meaningful locally connected features by using kernels smaller than the input, which allows units in deeper layers to preserve information from the input layer. Secondly, it applies the same

filters all over the input, thus permitting the learning of only one common set of parameters instead of many, as well as ensuring that the same learned representations can be found at different locations in the data. In addition to convolution, pooling in neighboring units in a layer can reduce the dimensions of the learned representation and makes it invariant to small perturbations in the input (LeCun *et al.* 2015; Goodfellow *et al.* 2016). Furthermore, regularization techniques help the learned features to better generalize to new unseen data, preventing model overfitting. One of the more effective and most frequently applied examples of regularization is Dropout (Srivastava *et al.* 2014), where noise is introduced in the output features of a layer aiming at inhibiting the network from learning non-meaningful patterns.

Traditional deep neural networks, including CNNs, are limited by having no memory, hence they cannot extract meaningful contextual information from sequentially structured data. Recurrent neural networks (RNNs; Rumelhart *et al.* 1986) overcome this constraint by simplistically mimicking human beings' mechanism for processing external information. They achieve this by implementing an internal loop that iterates over a sequence of data, element by element, while keeping an internal memory state of data they have already processed. The development of the long-short term memory RNNs (LSTMs) was one of the major breakthroughs in RNN architecture, since it solved the so-called vanishing gradient problem, whereby simple RNNs proved to be incapable of preserving long-term dependent information (Hochreiter & Schmidhuber 1997). By carrying information to later points in the sequence, LSTMs are capable of retaining patterns, and therefore learning, from very long sequences. LSTM models make use of internal dropout and recurrent dropout that help prevent overfitting, so improving model performance. Another significant advancement was the invention of Bidirectional RNNs (BRNNs; Schuster & Paliwal 1997), which

Table 1. Hyperparameter search space optimized during the training of phase detection models. The second column lists the hyperparameter values that could be sampled during the optimization. The third column shows the best-performing value found after 1000 trials. The hyperparameter *pre_mode* defines the type of filter applied to the seismic data before entering the network as follows: *pre_mode* = 1, 2, 3 correspond to no filter applied, bandpass filter (2–10 Hz), and high-pass filter (>0.2 Hz), respectively. Hyperparameters *win_size*, *frac_pre_P*, *frac_pre_S* and *frac_pre_N* control the length and time position of the extracted window samples used for the training, as described in the main text and Fig. 2. The range tested for the number of filters shown here relates only to the first convolutional layer. Another hyperparameter, not shown here, allows the number of filters in subsequent convolutional layers to be equal to or twice the value in the current layer.

Hyperparameter	Range tested	Best-performing value
<i>Convolutional layers</i>		
Number of layers	[1, 2, 3, 4, 5]	5
Number of filters	[2, 4, ..., 30, 32]	12, 24, 48, 96, 192
Kernel size	[3, 5, 7, 9, 11, 13, 15, 17, 19, 21]	17, 11, 5, 9, 17
Activation function	[ReLU, sigmoid]	ReLU, ReLU, ReLU, ReLU, sigmoid
Dropout	[0.2, 0.25, 0.30, 0.35, 0.4, 0.45, 0.5]	0.25, 0.25, 0.3, 0.4, 0.25
<i>Dense layers</i>		
Number of layers	[1, 2, 3, 4]	1
Number of units	[50, 100, 150, 200, 250, 300]	50
Activation function	[ReLU, sigmoid]	ReLU
Dropout	[0.2, 0.25, 0.30, 0.35, 0.4, 0.45, 0.5]	0.2
<i>Model training</i>		
Optimizer	[Adam, SGD, RMSprop]	RMSprop
Learning rate	[1e-05, 1e-04, 1e-03, 1e-02, 1e-01]	1e-03
Batch size	[50, 60, ..., 190, 200]	50
<i>Data pre-processing</i>		
<i>pre_mode</i>	[1, 2, 3]	1
<i>win_size</i> [s]	[2.0, 2.2, ..., 4.8, 5.0]	4.8
<i>frac_pre_P</i>	[0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]	0.7
<i>frac_pre_S</i>	[0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]	0.5
<i>frac_pre_N</i>	[0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]	0.9

make use of two recurrent layers to process sequences in both forward and backward directions. BRNNs can make learning more effective in sequences where both the past and future contexts can provide valuable insights.

In seismology, CNN models have been recently applied for detection (Ross *et al.* 2018a, b; Dokht *et al.* 2019; Woollam *et al.* 2019), association (McBrearty *et al.* 2019) and picking (Pardo *et al.* 2019; Zhu & Beroza 2018) of *P*- and *S*-wave arrivals, for earthquake localization (Kriegerowski *et al.* 2019; Perol *et al.* 2018; Mousavi & Beroza 2020b; Zhang *et al.* 2020), event discrimination (Mousavi *et al.* 2019b) and magnitude estimation (Mousavi & Beroza 2020a). RNN-based networks have been used for *P*-wave identification (Zhu *et al.* 2020), seismic phase association (Ross *et al.* 2019b) and for predicting approximate earthquake times and locations (Panakkat & Adeli 2009). Model architectures based on combinations of CNN and RNN networks have been implemented for earthquake detection (Mousavi *et al.* 2019c) and combined event detection and phase picking (Zhou *et al.* 2019; Zheng *et al.* 2020) tasks. Recently, novel models which apply attention mechanism on a CNN+LSTM-based network architecture (Mousavi *et al.* 2020c) and utilize a capsule neural network (Saad & Chen 2020) have also been used for combined event detection and phase picking.

This work adds to these previous studies, and introduces DeepPhasePick, an automatized two-stage method for detecting and picking seismic *P* and *S* phases from local earthquakes, entirely based on highly optimized deep neural networks. The first stage in DeepPhasePick consists of an adaptive CNN architecture trained for detecting the phases. Here the type of data pre-processing, as well as the length and position of the seismic phase windows used to train the network, were included among the optimizable hyperparameters. Phase picking is conducted in the second stage by applying two additional adaptive Bidirectional LSTM (BLSTM) networks, which were trained specifically to predict *P*- and *S*-phase time onsets. The onsets, and their uncertainties, are determined on time windows defined based on the predicted probabilities of the *P* and *S* phases in the detection stage.

Here we demonstrate how the optimized CNN network in the first stage of DeepPhasePick, trained on a rather small data set of labelled phases in comparison to previous studies, is able to detect with high accuracy *P* and *S* phases from local earthquakes of different tectonic regimes. We also show how, by leveraging the information of the detected seismic phases, the optimized BLSTM models trained for picking are able to predict *P*- and *S*-phase time onsets with analyst levels of precision, while also avoiding inherent human bias.

Figure 3. Estimation of time onset and associated uncertainty for predicted *P* (a–b) and *S* (c–f) phases. (a), (c), (e) Examples of predicted Z, E, N (Vertical, East, North) window samples, which correspond to the earthquake waveform shown in Fig. S1. Red and blue dashed lines represent the preliminary *P* and *S* onsets predicted in the phase detection stage, which were refined in the phase picking stage (red and blue solid lines). (b), (d), (f) Zoom in centred on the refined *P* and *S* time onsets ($tons_pred$ [s]), estimated by applying MCD ($T = 50$) inference. Predicted class probabilities for each MCD prediction are plotted as magenta curves (right y-axis); bold curve represents the mean probability. Magenta horizontal dashed lines indicate the mean (pb) and one standard deviation (pb_std) of the class probabilities at the onset time. As explained in the main text, from pb and pb_std , we can obtain $tons_pred$ and its uncertainty ($tons_err$ [s]), outlined by red and blue vertical dotted lines before and after the refined *P*- and *S*-phase onsets. Based on the weighting class scheme defined in Table 3, *P* and *S* phases shown here correspond to picks of class 0 and 1, respectively.

Table 2. Hyperparameter search space optimized during the training of *P*- and *S*-phase picking models. The second column lists the hyperparameter values that could be sampled during the optimization. The third and fourth columns show the best-performing values found after running 50 *P*- and *S*-phase optimization trials.

Hyperparameter	Range tested	Best value (<i>P</i> -picking)	Best value (<i>S</i> -picking)
<i>Recurrent BLSTM layers</i>			
Number of layers	[1, 2]	2	2
Units	[10, 20, ..., 190, 200]	100, 160	20, 30
Dropout	[0.2, 0.25, 0.30, 0.35, 0.4, 0.45, 0.5]	0.2, 0.35	0.25, 0.45
Recurrent Dropout	[0.2, 0.25, 0.30, 0.35, 0.4, 0.45, 0.5]	0.2, 0.25	0.35, 0.25
<i>Model training</i>			
Learning rate	[1e-05, 1e-04, 1e-03, 1e-02, 1e-01]	1e-04	1e-02
Batch size	[50, 60, ..., 190, 200]	60	50

Table 3. Weighting scheme for P and S predicted pick classes. Where $terr = \frac{1}{2}(|tons_err^-| + |tons_err^+|)$ is the mean of the absolute time uncertainties calculated before and after the phase onset shown in Figs 3(b) and (d) insets.

Quality class	Time onset error ($terr$ [s])
P0, S0	$terr < 0.05$
P1, S1	$0.05 < terr < 0.1$
P2, S2	$0.1 < terr < 0.2$
P3, S3	$terr > 0.2$

2 DATA AND METHODS

2.1 Earthquake catalogue data sets

In this study, we used two sets of manually picked event waveforms (Fig. 1). The first set (S1) consists of 1125 events from the time period between 1996-12-02T00:54:33.89 and 1997-11-20T02:24:59.41 (Schurr *et al.* 2006). The second set (S2) contains 1196 events which occurred from 2007-06-14T01:18:52.24 to 2007-12-13T07:23:39.24 in the area of the 2007 $M7.7$ Tocopilla earthquake (Schurr *et al.* 2012). S2 contains mostly plate interface events, whereas S1 contains mostly intermediate-depth intraplate events.

From these earthquake catalogues, we extracted three-component seismograms which we subdivided into three window classes: 25 647 P -phase, 25 647 Noise (N) and 14 397 S -phase windows. 16 234 P, 16 234 N and 8061 S of these samples were obtained from S1, and 9413 P, 9413 N and 6336 S samples from S2. We used these seismic windows as input data to train adaptive neural networks in phase detection and phase picking tasks, as will be described in the next sections.

2.2 Hyperparameter optimization of adaptive neural networks

The architecture of a neural network is defined by its hyperparameters, such as the number of layers in the network, the training learning rate and the batch size used during training. The selection of the model hyperparameters is key when implementing a supervised deep learning task, since it may lead to a significant improved performance of the trained model, especially when the available data is limited.

Commonly used hyperparameter optimization approaches, which rely on grid or manual search, have been shown to be less efficient than an optimization based on random search (Bergstra & Bengio 2012). However, all the above mentioned methods select the subsequently sampled values without an informed criterion. This makes the optimization less effective, since the sampling of hyperparameter values which do not lead to improved performance tends to require a significant amount of time. In contrast, Bayesian optimization selects the next sampled hyperparameters based on previous evaluations. This has proven more efficient in terms of balancing exploration-exploitation of the search space, time consumption and model performance results, compared to random search (Bergstra *et al.* 2013a; Hinz *et al.* 2018).

In Bayesian optimization, an objective function is minimized by mapping past evaluations of the hyperparameters to a surrogate probabilistic model of the objective function, which is then more simply optimized instead. In this work, we used a Bayesian approach that optimizes a surrogate model defined by the Tree Parzen Estimator (TPE) algorithm, as implemented in the Python library

Hyperopt (Bergstra *et al.* 2013b). Basically, TPE algorithm applies the Bayes rules to create two different probability distributions for the hyperparameters, depending on the score reached by the objective function. The next set of sampled hyperparameters is then selected based on the expected improvement in the objective function (Bergstra *et al.* 2011).

We implemented two types of objective functions, which are minimized in order to optimize the training of different adaptive neural network architectures designed to solve two tasks: phase detection and phase picking. These architectures will be described in detail in the next sections. The hyperparameter optimization process was performed using one GPU NVIDIA GeForce RTX 2080. Multiple iterations (trials) were run for each task, with a different hyperparameter configuration being attempted in each trial, until a best-performing trained model, that is a model with minimum error, was found. The adaptive neural networks were built in Python using the machine learning framework Keras (Chollet 2015) with Tensorflow as backend (Abadi *et al.* 2015).

2.3 Phase detection as a supervised multiclass classification task

We implemented the phase detection stage as a supervised multiclass classification task, based on an adaptive neural network formed by two blocks of deep layers. The first block is made up of between one and five convolutional layers, which extract abstract representations (features) from three-component seismograms input (samples) and help reduce their dimensionality. The output of the convolutional layers is then flattened before entering the second block, formed by between one and four dense (fully connected) layers. All the units in a fully connected layer are connected to all the units in the preceding layer. This allows them to better learn correlated features throughout the input data, rather than only the locally connected features learned by convolutional layers. Hence, dense layers are well suited for the final classification stage in the adaptive network. Since the network is adaptive, the number of layers in each block, as well as specific layer variables such as the number of convolutional filters or dense units, are adjusted during the hyperparameter optimization.

We chose to use depthwise separable 1-D convolutional layers for the feature extraction in the first block. Depthwise separable convolutional layers implement a 2-step convolution process, first performing independent convolutions on each channel of the input data and then combining individual channel outputs through a pointwise (1×1) convolution (Chollet 2017). This type of convolution is appropriate for learning patterns from multicomponent seismic data, such as 1-D amplitude time-series from seismic waveforms, since different features can be extracted from the three input channels (the three components of each seismogram) independently. This may help the network extract specific patterns from, for example the two horizontal components, in order to better identify S phases. Furthermore, compared to standard convolutional layers, depthwise separable layers have the additional advantage of helping reduce model overfitting, since they have fewer weights to adjust, and therefore require fewer calculations. This further reduces the overall computational cost, since less calculation time is required to complete the multiple iterations over different network architectures involved in the hyperparameter optimization.

Outputs from each of the convolutional and dense layers in the network, except from the output of the final dense layer, are passed through a layer that applies a non-linear activation function that

Figure 4. Distribution over the 1000 optimization trials of the six main hyperparameters used in the phase detection model training. Subplots show sampled hyperparameter values coloured by trial number and plotted versus the model accuracy reached at that trial (left y-axis). The distribution of the hyperparameter values sampled over the trials is presented as a histogram (right y-axis). A grey shaded bin in the histogram represents the best-performing hyperparameter value, that is, the value with which the model reached the highest accuracy.

can be either a rectified linear unit (ReLU; Nair & Hinton 2010) or a sigmoid, according to the hyperparameter selection. Additional Batch Normalization (Ioffe & Szegedy 2015) and Dropout (Srivastava *et al.* 2014) layers are stacked to the activation outputs in both blocks. In the convolutional block, a further 1-D Max Pooling layer is applied between each Batch Normalization and Dropout

layer. The output of the final dense layer is passed instead through a softmax activation function. This outputs a vector of three probabilities, adding up to 1.0, each expressing the likelihood of a sample belonging to one of the three possible classes tested: P, S or N. The greatest among these probabilities determines the predicted class of the three-component record.

Figure 5. Each subplot depict in detail the distribution of the best-performing hyperparameter values (grey shaded bins in histograms of Fig. 4; blue circles) that led to higher model accuracies (>0.95) over the trials. Values plotted are the accuracies on the validation set, reached at the end of each trial training. For the hyperparameters in which the best-performing value does not coincide with the most frequently sampled value, the latter are plotted as well (red circles). For reference, magenta horizontal and vertical dashed lines mark the highest model accuracy (0.990) reached during the optimization and the trial (733) at which it was achieved, respectively.

Prior to initializing the optimized training, we randomly extracted an independent test set consisting of 1440 P, S and N three-component time-series windows, made up of 888 records from S1 and 552 records from S2 data sets for each class, so as to keep the proportion of samples present in each data set. In order to reduce the possibility of biased phase classification due to an imbalanced class distribution in our data set (39 per cent P, 39 per cent N, 22 per cent S), the remaining data was balanced out at each optimization trial

by randomly discarding the surplus samples of the over-represented P and N classes. Then, the balanced data was shuffled and assigned to the training and validation sets before carrying out the model training. The resulting training, validation and test sets added up to 75 per cent (32 393), 15 per cent (6478) and 10 per cent (4320) of the total balanced data samples, respectively. During the training, features of the waveforms were learned from the training set and the weights in the network layers were adjusted based on this. The

Figure 6. Optimized model architecture trained for phase detection task. The network receives as input class vectors representing the respective accompanying three-component seismogram samples and outputs three-probability vectors indicating the predicted classes (P, S or N). The optimized hyperparameters in each block of convolutional and dense layers are shown here and also presented in Table 1.

Figure 7. (a and b) Results from evaluation of the best phase detection model on the independent test set of 4320 samples, represented in a confusion matrix (a) and a precision-recall curve (b). In (b), AUC represents the area under the precision-recall curve for each class. Precision, Recall and F1-score at two probability thresholds are reported in Table S1. (c) disaggregated histograms of incorrectly predicted *P* or *S* phases as noise and presumably misclassified noise samples as *P* or *S* phases. (*P*, *N*) means *P*-phase samples predicted as Noise, and similarly for other cells in the confusion matrix.

Figure 8. (a) Example of *P*-phase sample in the test set of 4320 samples, mispredicted as noise (N). (b) Example of *S*-phase sample in this test set, mispredicted as noise. The left subplots in (a) and (b) show the three-component seismic waveform from which the samples were extracted. The extracted samples, as received by the network, are shown in the right subplots. Examples shown here correspond to *P*-phase and *S*-phase samples with analyst's pick weights 2 (50 per cent confidence) and 1 (75 per cent confidence), respectively.

updated model was then used to predict the sample classes in the validation set, and adjust the model hyperparameters accordingly. The final performance of the best trained model was evaluated using the test set. We assigned to each sample in the training, validation and test sets, binary vectors representing the sample class as follows: [1, 0, 0] for *P* class [0, 1, 0] for *S* class, and [0, 0, 1] for *N* class. These vectors were used as the known labels which were compared with the vector of class probabilities predicted by the model.

During each optimization trial, seismic data was linearly detrended, resampled at 100 Hz and filtered. The type of filter applied to the data is defined by the currently sampled value of the hyperparameter *pre_mode*, and can be band-pass (2–10 Hz), high-pass (>0.2 Hz), or no filter. Next, the sample windows were extracted as defined by the sampled *win_size*, *frac_pre_N*, *frac_pre_P* and *frac_pre_S* hyperparameter values. The hyperparameter *win_size* defines the length of the extracted windows (2–5 [s]), which we imposed to be equal for the three classes. This makes data manageable by the network during the training. The three additional hyperparameters (*frac_pre_N*, *frac_pre_P* and *frac_pre_S*) vary between 0.2 and 1.0 and define the fraction of the extracted windows that is placed before the event origin time, the true *P*-phase onset and the true *S*-phase onset for classes *N*, *P* and *S*, respectively (see Fig. 2). Then the extracted sample windows were normalized by the maximum amplitude across the three waveform components and subdivided in the training, validation and test sets, as explained above.

The training and validation sets were then used to train the model configuration defined by the rest of the hyperparameters sampled in the trial.

The total space of hyperparameters searched during the optimization is presented in Table 1. In order to search for the best-performing network trained in detecting seismic phases, we ran 1000 hyperparameter optimization trials (~9 min per trial). In each trial we used the validation accuracy as the optimizable metric and we trained the model for up to 60 epochs using the categorical cross-entropy loss function. To speed up the training process, we additionally applied an early stopping callback that stopped the training if the validation accuracy did not increase in 6 epochs.

2.4 Phase picking as a supervised sequence binary classification task

As mentioned previously, phase picking in DeepPhasePick uses two optimized adaptive network architectures, each formed by one or two BLSTM layers, which we implemented as a supervised sequence binary classification task.

We trained a first model for picking *P* phases, using as input the amplitude time-series taken from vertical-component seismograms. A second model was trained for picking *S* phases, based on the amplitude time-series of the two horizontal-component records. We trained each model to learn patterns from seismic data that account

Figure 9. (a) Example of noise (N) sample in the test set of 4320 samples, seemingly mispredicted as a *P*-phase. (b) Example of noise sample in this test set, seemingly mispredicted as a *S*-phase. Subplots are plotted the same way as in Fig. 8. The apparent misclassifications shown here are examples of non-picked phases, which were however detected by the network.

for the transition from noise to signal in both *P* and *S* phases from local earthquakes, therefore allowing identification of *P* and *S* time onsets. BLSTM-based networks are suitable for such task, since they are able to retain and learn sequential characteristics while processing input seismic time-series in both chronological and antichronological order, hence learning dependencies between phase onsets and neighboring seismic patterns. A final dense layer in both picking models applies a sigmoid activation function, which outputs the probability of the time steps in the time-series corresponding to either noise or seismic signal.

Before carrying out the model training, 10 per cent of the window samples were randomly extracted as an independent test set. As in the phase detection stage, the test set includes a proportional amount of records from S1 and S2 data sets. The remaining samples were first shuffled and then subdivided into training (65 per cent) and validation (25 per cent) sets. Altogether, this corresponds to 16 670 training, 6412 validation and 2565 (1625 from S1, and 940 from S2) test one-component samples for *P*-picking; and 9358 training, 3599 validation and 1440 (808 from S1 and 632 from S2) test two-component samples for *S*-picking. As in the phase detection stage, weights and hyperparameters of the models were adjusted based on the training set and validation set, respectively. The test set was then used to evaluate the performance of the best trained models. The window samples were defined based on the optimized hyperparameter values for the phase detection model, namely the window length (*win_size*) and its relative

position with respect to the true onset (*frac_pre_P* and *frac_pre_S*). This allows the integration of phase detection and phase picking in a common two-stage workflow, with the aim of making the overall process more efficient, since both stages share already optimized information.

However, instead of using the above-described seismic windows, we trained and validated the picking models on versions of them, which were randomly shifted in time by a range between -0.5 and 0.5 [s] around the true *P* and *S* onsets. This allows the networks to better learn data patterns in the vicinity of the phase onsets, and so preventing the model from memorizing only fixed onset times. A similar approach has been applied by Ross *et al.* (2018a) by using an artificially augmented number of samples to train a CNN network as regressor for *P*-phase picking. In the test set, we kept both the original time windows and their shifted versions, in order to test the detection capacity of the trained models in both scenarios.

So as to perform the model training, we assigned to each input sample a binary vector of length equal to the sample window length. This vector is a binary representation of the ground truth, where all the 0s correspond to time steps associated to noise, and all the 1s representing signal, so that the first 1 represents the time step of the true phase onset. Once trained, the models output a vector of the same length, which contains numbers between 0 and 1.0 corresponding to binary class probabilities: <0.5 for time steps predicted as noise and >0.5 for time steps predicted as signal. Thus, we can determine the predicted phase time onset in a given sample

Figure 10. Optimized model architectures trained for *P*-phase (a) and *S*-phase (b) picking tasks. The networks receive as input binary vectors representing the noise (0) and signal (1) content in accompanying time-series taken from the vertical-component (a) and the two horizontal-component (b) seismograms of the samples used for training. The models output is the probability of the time steps in input samples corresponding to either noise or seismic signal. The optimized hyperparameters in each BLSTM layer are shown as (Units, Dropout, Recurrent dropout), which are also reported in Table 2 for both models.

as the time step where the output probabilities first rise above 0.5, indicating a change from noise to signal.

We ran 50 hyperparameter optimization trials for the *P*- (~130 min per trial) and *S*-phase (~50 min per trial) picking tasks. Table 2 presents the hyperparameter space searched during the optimization. We optimized on the validation accuracy metric, using the binary cross-entropy loss function and the Adam stochastic optimization algorithm (Kingma & Ba 2014) in the training. The training was carried out using the same number of epochs and similar early stopping as in the phase detection stage.

2.5 From predicted phase probabilities to preliminary onsets

By applying our best-performing models trained for both phase detection and phase picking on continuous seismic data, we were able to obtain the time onsets of *P* and *S* phases originating from local earthquakes. In this section we explain how we first obtained preliminary time onsets in the phase detection stage. The next section describes how we refined them in the phase picking stage to estimate the final phase onsets and their associated uncertainties.

First, we used the optimized phase detection model to predict the class probabilities of three-component moving windows. By iteratively shifting these windows along the continuous seismic waveforms, we obtained a discrete probability time-series of each class. The length of the moving window is given by the optimized hyperparameter *win_size*. We assigned the predicted probability at the

position within the window defined by the optimized hyperparameters *frac_pre_N*, *frac_pre_P* and *frac_pre_S* for the respective classes (see Table 1, and Figs 2 and S1). The time step between consecutive moving windows is a user-defined parameter that controls the resolution of the probability time-series.

Next, we declared a *P*-phase search window between the time where the *P*-class probability time-series (*pb_P*) rises above certain trigger threshold *pb_P_th1* and the time where *pb_P* decreases below a certain det trigger threshold *pb_P_th2*. We estimated a preliminary *P*-phase onset as the time of the maximum *pb_P* within the search window. For waveforms where a preliminary *P* onset is found, we followed a similar approach to define a preliminary *S*-phase onset at the time of the maximum *S*-class probability time-series (*pb_S*), within an *S*-phase search window delimited by the time interval that satisfies the condition $pb_S_th1 < pb_S < pb_S_th2$. Cases where *pb_P* and *pb_S* overlap or are close enough in time at values above the trigger thresholds cannot be handled solely with the previous criteria. We included few additional conditions, based on the predicted probabilities, to deal with this and other particular scenarios. These conditions can be optionally activated by the user and depend on a few user-defined parameters (see Text S1).

2.6 Estimation of final phase onset times and their uncertainties

The preliminary *P* and *S* onsets were defined based on probabilities returned by a model trained for recognizing seismic phases, rather

Figure 11. Evaluation of the optimized model trained for *P*-phase picking on the independent augmented test set of 2565×2 one-component waveform samples. (a) True time onsets (*tons_true*) from both the actual and shifted samples forming the augmented test set. (b) Predicted time onsets (*tons_pred*), defined as in Fig. 3 by the best model trained for *P*-phase picking. (c) Time residuals (*tres*) distribution, defined as the difference between the true and predicted time onsets. Reported mean (μ), standard deviation (σ) and mean absolute error (MAE) are calculated on this residual distribution ($|tres| \leq 0.8$). Here we considered $MAE = \frac{1}{n} \sum_{i=1}^n |t_i - \hat{t}_i|$, where t_i and $\hat{t}_i$ are the predicted and true onsets of n samples, respectively. (d) Predicted pick quality classes, as defined by weighting scheme defined in Table 3.

than for actually picking them, and therefore need to be refined. To this end, we used ‘picking windows’ of length *win_size*, as defined by the optimized hyperparameters *frac_pre_P* and *frac_pre_S* around the preliminary *P*- and *S*-phase onsets. On these picking windows, we then applied the optimized models trained for *P*- and *S*-picking to estimate the respective phase onsets as well as the associated uncertainties.

Uncertainties were determined by applying the stochastic regularization technique Monte Carlo Dropout (MCD). It has been shown that using dropout at testing time of a deep neural network can be interpreted as a Bayesian approximation of a Gaussian process, hence MCD can be used as an approximation of Bayesian variational inference (Gal & Ghahramani 2016a, b). This means that a model posterior distribution for a given sample can be represented by multiple (*T*) predictions made by the network with dropout. Thus, the value and uncertainty of the predicted sample can be obtained as the mean and standard deviation of the *T* inferences.

In practice, we implemented MCD by performing *T* model predictions with dropout. In this case, since phase picking is treated as a sequence binary classification task, MCD generates a collection of predicted class probabilities of the time steps in an input time-series. This collection is an approximation of the model posterior distribution for that input sample, which is described by the mean and standard deviation of the *T* class probabilities at each of the sample time steps.

Then, we estimated the predicted phase time onset (*tpred*) for the sample as the first time step in which the mean of the class probabilities rises above 0.5 (*pb*), which indicates the predicted transition from noise to signal. The standard deviation of the class probabilities at *tpred* (*pb_std*) represents the variability of the predicted probability at the assumed time onset. We propose that a reasonable first order estimation for the time onset uncertainty can be determined as the interval of time steps delimited before and after *tpred* by the projection of *pb_std* on the mean class probability (see

Figure 12. Evaluation of the optimized model trained for *S*-phase picking on the independent augmented test set of 1440×2 two-component waveform samples. Subplots are similar as in Fig. 11.

Fig. 3). The resulting time uncertainty is asymmetric and inversely proportional to the slope of the mean predicted probability curve around $tpred$. That is, the steeper the decrease/increase in the predicted probability before/after $tpred$, the lower the time uncertainty, as one might intuitively expect from an abrupt, easy-to-pick change from noise to signal. Based on these estimated pick uncertainties, we defined the weighting class scheme for the phases *P* and *S* shown in Table 3, which was adapted from (Sippl *et al.* 2013).

3 RESULTS

3.1 Phase detection model optimization

Fig. 4 summarizes how the six main hyperparameters in the phase detection model evolved over the 1000 optimization trials attempted. For the majority of the main hyperparameters, the most frequently sampled hyperparameter value (higher histogram bins) did not coincide with the value that led to the highest model accuracy found after 1000 trials (shaded histogram bin), although this correlation was observed for the number of convolutional layers and *frac_pre_P*.

Remarkably, as can be seen from the subplots in Fig. 5, the best hyperparameter values or the most frequently sampled values (when both did not coincide) formed clusters at several times (around trials 150, 260, 400, 590 and 800) during the optimization. This suggests that the same set of hyperparameter values was systematically found to be effective in producing highly accurate models during the optimization process, while the rest of the hyperparameters in the network were probably still being adjusted.

The best-performing hyperparameter values indicate that models in which the convolutional block was considerably deeper (five convolutional layers) than the dense block (only one or two dense layers) proved to be more accurate. Furthermore, models that learned from band-pass filtered data reached lower training accuracy in comparison to when high-pass filter or no filter was applied, with the latter approach performing the best. Thus, using the whole frequency content proved to be more effective for model training than removing very long period background seismic noise or substantially limiting the frequency content. We note here that quite a few of the data are from short-period seismometers, hence inherently high-pass filtered (> 1 Hz), which could account for the most frequently sampled value of *pre_mode*.

Figure 13. (a), (c) Normalized distribution of analyst P- and S-pick quality classes over the range of predicted time onset errors (*terr* in Table 3). Time errors were predicted on the augmented test sets, so analyst quality classes are counted twice. Points defining each coloured curve are plotted at the centre of the histogram bins corresponding to each pick class distribution. Dotted vertical black lines mark the time confidence interval limits used in the weighting scheme to assign the predicted pick classes (Table 3). (b), (d) Histograms (bin size = 0.05 [s]) showing disaggregated distributions of analyst P- and S-pick classes shown in (a) and (c), respectively.

Another important constraint in the optimization process seems to be the amount of data available for the network to learn, since longer window samples (480–500 s) clearly led to more correctly predicted phases. *P* phases were more accurately predicted when the sample windows include a relatively larger portion of noise (70 per cent) compared to signal, whereas *S* phases were better predicted from windows containing similar amount of noise relative to signal (50 per cent).

Table 1 lists the best-performing values found for each of the optimized hyperparameters, which were used to train the best phase detection model architecture outlined in Fig. 6.

3.2 Predicted phase classes compared to analyst labels

Figs S2(a) and (b) show that the accuracy of the best phase detection model smoothly increased on the training set and reached 0.986 after 35 epochs, when the early stopping condition stopped the training. The training loss progressively decreased and reached

0.044 at the end of the training. The accuracy and loss calculated on the validation set followed a similar behavior to the training curves, although showing overall higher accuracy and lower loss due to the use of dropout regularization during training. Dropout disables a certain number of layer units, therefore some information about the input samples is lost and the network attempts to learn based on incomplete data representations. However, during validation all the units are available, thus the network uses its full computational power.

The confusion matrix in Fig. 7(c) shows the overall performance of the best trained model in classifying the classes of the independent test set of 4320 samples. The cells in this matrix are filled with the predicted classes, which correspond to the highest of the three-class probabilities returned by the model for each sample. An overall very high ratio (0.99) of correct predictions is observed for the three classes, as can be seen from the numbers in the matrix diagonal. Fig. S3 show waveform examples of these correctly predicted P-, S- and N-class samples.

Figure 14. Automatically derived earthquake catalogues in northern Chile, from which two independent test sets of three-component samples were used to evaluate the DeepPhasePick performance. A first test set of 228 230 samples was extracted from events occurring between 2013-06-01 and 2014-02-28 (T1: red circles; Sippl *et al.* 2018). A second test set of 1 361 544 samples was taken from events occurring between 2014-03-01 and 2014-12-31 (T2: green circles; Soto *et al.* 2019). Window samples obtained from T1 and T2 were registered by the 21 and 82 stations shown on the map. Focal mechanisms (beachballs) and epicentres (stars) of the Iquique M8.1 main shock, its largest M6.6 foreshock and its largest M7.6 aftershock (Hayes *et al.* 2014) are plotted for reference in orange, yellow and brown colour, respectively.

Of the few misclassified samples, only three correspond to *S* phases predicted as *P*, whereas no *P* phases were mispredicted as *S*, indicating that the network has a high capability to discriminate between both classes. Fig. S4 shows one of these misclassified *S* phases, where the pick made by the analyst was somewhat earlier than the most impulsive change in amplitude. This could be one possible source of misclassification between the two phases, since it may have led to the network misinterpreting the sample as a *P* phase.

The remaining mispredictions correspond to either actual *P* or *S* phases predicted as noise (24 samples) or presumed noise predicted as *P* or *S* phases (21 samples). From the samples in the former group, the majority of the *P* (90 per cent) and *S* (~71 per cent) samples were assigned pick weights higher or equal than 1 (<75 per cent confidence) by analysts (Fig. 7e). This is indicative of waveforms with relatively low signal-to-noise ratio (SNR), as can be seen from the examples of mispredicted *P* and *S* phases shown in Figs 8(a) and (b), which may cause the model misclassification. In the latter

Figure 15. Results from the evaluation of the best model trained for phase detection on independent test sets taken from automatically derived earthquake catalogues T1 (a–b) and T2 (c–d). (a), (c) Confusion matrices. (b), (d) disaggregated histograms of incorrectly predicted *P* or *S* phases as noise (upper subplots) and presumably misclassified noise samples as *P* or *S* phases (lower subplots). (*P*, *N*) means *P*-phase samples predicted as Noise, and similarly for other cells in the confusion matrix.

group, a significant majority of the noise samples were predicted as signal with relatively high probability. In fact, of these, 87.5 per cent of the *P* and ~77 per cent of the *S* predictions had a probability higher than 0.7, with 75 per cent of the *P* and 38 per cent of the *S* predictions having a probability higher than 0.9 (Fig. 7e). The examples in Figs 9(a) and (b) demonstrate that these apparently mispredicted samples actually correspond to previously undetected phases, hence evidencing the powerful detection capacity of the model.

The detection capability of the trained model can be further assessed by calculating the precision and recall metrics. Precision, given by $TP/(TP + FP)$, describes how well the model predicts a specific class, by comparing the correct predictions of the class (true positives: *TP*) with all the predictions made for that class ($TP + FP$; where *FP* means false positives). Recall is computed as $TP/(TP + FN)$ and reports the ability of the model to identify all the samples of a given class, by comparing *TP* with all the samples of that class in the test set ($TP + FN$; where *FN* are false negatives).

Precision and recall vary between 0 and 1, where higher values are associated with better performing models. In a precision-recall curve, precision is plotted against recall for different probability thresholds, that is the probability above which a sample is predicted to be of a certain class. The more the curve bends toward the point (1, 1), and therefore the larger the area under the curve (AUC), the better the model performance. Fig. 7(d) shows the precision-recall curve obtained for the samples in the independent test set. As can be seen here the performance of the model in predicting both *P*- and *S*-class samples was very high, with the performance being slightly better for the *P* than for the *S* class. The model performance on *N*-class samples was somewhat lower. However, this calculated performance does not take into account any presumed *N*-class samples where the model detected a real seismic signal. As previously discussed by Ross *et al.* (2018b), the probability threshold can be tuned so as to improve precision (reducing false positives) or recall (aiming at reducing missed detections), depending on the application.

Figure 16. Results from the evaluation of the optimized model trained for *P*-phase picking on independent augmented test sets formed by 1000×2 samples taken from the automatically derived earthquake catalogues T1 (a and b) and T2 (c and d). (a) *P*-phase time residuals distribution for test samples taken from T1 (as in Fig. 11c). (b) *S*-phase time residuals distribution for test samples taken from T1 (as in Fig. 12c). (c) *P*-phase time residuals distribution for test samples taken from T2. (d) *S*-phase time residuals distribution for test samples taken from T2.

3.3 Predicted phase time onsets compared to analyst picks

Table 2 shows the best-performing hyperparameter values found during the optimization of the *P*- and *S*-phase picking models. These parameters were used to train the best picking model architectures outlined in Figs 10(a) and (b).

At the end of the training, the best *P*-picking model reached higher accuracies (0.983 in training) than the accuracies of the *S*-picking model (0.972 in training). This is also reflected in the training and validation loss functions, which reached a lower value for *P* phases (0.041 in training) than for *S* phases (0.066 in training, Fig. S2). As previously explained, the MCD estimation of predicted phase time onsets and their uncertainties requires that the picking models are trained with dropout. For this reason the training and validation curves do not show the difference in accuracy and loss observed for the best phase detection model.

Figs 11 and 12 summarize the performance of the optimized models trained for picking *P* and *S* phases, when evaluated on the independent test sets of 2565 one-component and 1440 two-component samples respectively. In order to evaluate how the models perform

in different possible picking scenarios, we used an augmented test set formed by two groups of samples: (1) the actual waveforms in the original test set, as defined by the optimized hyperparameters of the best phase detection model (*win_size*, *frac_pre_P* and *frac_pre_S*) and (2) artificial versions of the same waveforms, randomly shifted between -0.5 and 0.5 s around the true phase onsets made by the analysts.

The slightly higher accuracy reached by the *P*-phase picking model is reflected in the shape of the true and predicted time onset distributions, which more closely resemble each other for the *P*-phase (Figs 11a and b) compared to the *S*-phase (Figs 12a and b). Consequently, a narrower distribution of time residuals was obtained for *P* phases compared to *S* phases (Figs 11c and 12c). Overall, however, the time residual distributions for both *P* and *S* phases show a remarkable compliance with analyst picks. Based on the weighting class scheme defined in Table 3, we observe that a significant majority of *P*- and *S*-phase onsets were predicted with lower uncertainties (pick quality classes 0 or 1 in Figs 11d and 12d). Even though the distributions of all pick quality classes span over

Figure 17. (a), (b) Cumulative number of P (red curve) and S (blue curve) phases predicted by DeepPhasePick ($pb_P_th1 = pb_S_th1 = 0.98$), and triggered detections by the STA/LTA algorithm (green curve) on continuous seismic data recorded at the PB06 station (a) and across all IPOC stations with available data (b). Cumulative curves are plotted for the time interval covering two months before up to two months after the 2007 $M7.7$ Tocopilla main shock (2007-11-14), which is marked as a magenta dashed line. An orange dashed line indicates the time of occurrence of a $M7.1$ aftershock (2007-12-16) ~ 50 km south of the main shock epicentre. (c) 1-hr waveform snippet of PB06 station data, depicting the phases predicted by DeepPhasePick ($pb_P_th1 = pb_S_th1 = 0.98$) at the time indicated by the arrows in (a) and (b): red and blue lines represent P and S phases, respectively.

Figure 18. (a), (b) Cumulative number of P (red curve) and S (blue curve) phases predicted by DeepPhasePick ($pb_P_th1 = pb_S_th1 = 0.98$), and triggered detections by the STA/LTA algorithm (green curve) on continuous seismic data recorded at the PB01 station (a) and across all IPOC stations with available data (b). Cumulative curves are plotted for the time interval covering 2 months before up to two months after the 2014 $M8.1$ Iquique main shock (2014-04-01), which is marked as a magenta dashed line. Two additional orange dashed lines indicate the time of occurrence of the largest foreshock ($M6.7$; 2014-03-16) and aftershock ($M7.6$; 2014-04-03) in the Iquique sequence. (c) 1-hr waveform snippet of PB01 station data, depicting the phases predicted by DeepPhasePick ($pb_P_th1 = pb_S_th1 = 0.95$) at the time indicated by the arrows in (a) and (b): red and blue lines represent P and S phases, respectively.

a similar range of time residuals, the distribution is more flattened for higher uncertainties. This may suggest that picks predicted with lower uncertainties by the network were also easier to pick by the analyst (possibly due to a waveform with higher SNR), resulting in lower time residuals since both the network and analyst would have picked a similar onset. Conversely, picks that were harder to pick by the analyst (e.g. due to a waveform with lower SNR), were

probably predicted with higher uncertainties by the network, which would lead to higher absolute residuals.

So as to investigate this correlation between predicted and analyst pick classes, we plotted the distribution of the analyst pick classes against the predicted time onset errors ($terr$) for both test sets (Fig. 13). Essentially, these distributions show that analyst classes do not always correlate with equivalent predicted

Figure 19. (a), (b) Cumulative number of P (red curve) and S (blue curve) phases predicted by DeepPhasePick ($pb_P_th1 = pb_S_th1 = 0.98$), and triggered detections by the STA/LTA algorithm (green curve) on continuous seismic data recorded at the AB21 station (a) and across all Albanian stations with available data (b). Cumulative curves are plotted for the time interval between 2019-12-19 and 2020-02-24, during the aftershock sequence of the 2019 $M6.4$ Albania earthquake (2019-11-26). (c) 1-hr waveform snippet of AB21 station data, depicting the phases predicted by DeepPhasePick ($pb_P_th1 = pb_S_th1 = 0.98$) at the time indicated by the arrows in (a) and (b): red and blue lines represent P and S phases, respectively. (d) Green dashed lines depict the STA/LTA detections produced on the 1-hr waveform plotted in (c).

classes, but instead span the entire range of predicted time onset errors.

However, a couple of observations from the normalized distributions in Figs 13(a) and (c) may indicate that at least some degree of correlation does exist. First, lower-uncertainty analyst picks (classes 0 and 1) concentrate in predicted lower-error intervals ($terr < 0.05$) in a considerably higher proportion, compared with higher-uncertainty analyst picks (classes 2 and 3). Second, analyst picks of higher uncertainty decrease more gradually and rise above picks of lower uncertainty when $terr > 0.05$.

3.4 Evaluation on independent test sets from automatically derived earthquake catalogues

We further analysed the performance of the best trained models of DeepPhasePick on two additional independent test sets. These test sets consisted of three-component window samples extracted from two earthquake catalogues recently published for the region where the 2014 $M8.1$ Iquique megathrust earthquake ruptured the northern Chilean subduction on 1 April 2014 (Fig. 14). The first

catalogue (T1) contains 8278 events occurring in a time window of nine months before the Iquique main shock (between 2013-06-01 and 2014-02-28, Sippl *et al.* 2018), from which we extracted 228 230 records (P : 88 449; N : 88 449; S : 51 332). The second catalogue (T2) includes 18 963 events originating between 1 month before and 9 months after the main shock (between 2014-03-01 and 2014-12-31, Soto *et al.* 2019), from which we obtained 1 361 544 records (P : 545 746; N : 545 746; S : 270 052). Event records extracted from T1 and T2 were automatically picked by applying conventional state-of-the-art phase picking algorithms (Aldersons 2004; Di Stefano *et al.* 2006; Diehl *et al.* 2009), thus provide a valuable quantitative assessment when compared to DeepPhasePick predictions.

We first analysed the performance of the optimized model trained for phase detection. For this analysis, we used test sets formed by the entire set of samples available from catalogues T1 and T2. Fig. 15 summarizes the classification results from the evaluation of the model on both test sets. In the confusion matrices in Figs 15(a) and (c), we observe the highest ratio of correct predictions for noise samples, comparable to the evaluation performed on the test set extracted from data sets S1 and S2 (Fig. 7c). The percentage of

Figure 20. Example of multistation phase prediction made by DeepPhasePick ($pb_P.th1 = pb_S.th1 = 0.98$) on continuous seismic data in Albania. Red and blue lines mark predicted P and S phase time onsets, respectively. Horizontal north component (grey) is plotted on top of vertical component (black) in each station waveform. Several events are clearly detected across the station network.

correct classifications decreased by 8–15 per cent for P samples and 17–19 per cent for S samples.

From the mispredicted P and S records, only a small fraction corresponds to P phase mispredicted as S , or vice versa, compared to the number of P and S records which were predicted as noise. As we observed for the results in Fig. 7(c), the optimized model can mispredict S phases as P phases if the true S time onsets are somewhat earlier. Conversely, it is conceivable that the network classifies a P phase as an S phase if the true P time onset is late.

P and S phases predicted as noise correspond almost entirely to samples which were assigned automatic pick quality class 1 or worse (<75 per cent confidence), with most of them being assigned the poorest pick quality class (class 3; <25 per cent confidence) (upper subplots in Figs 15b and d). As we have discussed, the classification of these hard-to-pick phases by the network appears to be challenging. Moreover, about half of the few apparently misclassified noise samples were predicted as P or S phases with a probability of at least 90 per cent (lower subplots in Figs 15b and d), suggesting that these presumed noise records might actually represent phases previously undetected by the automatic detection procedure, similar to the examples shown in Fig. 9.

We next analysed the performance of the optimized models trained for P - and S -phase picking, using test sets formed by 1000 P - and S -phase samples randomly selected from T1 and T2 catalogues. As described in the previous section, the picking models were evaluated on augmented versions of these test sets.

Results from the picking predictions are summarized in Fig. 16. Time residual distributions, which are narrower for P phases

(Figs 16a and c) compared to S phases (Figs 16b and d), are observed in both test sets. Similar distribution shapes were obtained for the augmented test set derived from S1 and S2 data sets (Figs 11c and 12c), hence evidencing that the trained picking models generalize effectively to different data sets.

3.5 Prediction on continuous seismic waveform data

After analysing the performance of DeepPhasePick with different independent sets, we used the best-performing trained models in the algorithm to carry out the phase detection and picking tasks on continuous seismic data recorded in two different tectonic environments. First, we applied DeepPhasePick on data which covers the time of two megathrust earthquake sequences that occurred in the northern Chile subduction zone (2007-11-14 M7.7 Tocopilla and 2014-04-01 M8.1 Iquique main shocks). In this case, the data used was recorded by network stations situated in desertic areas, far from cities, and therefore exposed to low background seismic noise. Next, DeepPhasePick was applied on seismic data that partly covers the aftershock series of a recent M6.4 earthquake which occurred on 2019-11-26 near the port town in Durres, Albania, in a region of convergence between Adriatic and Eurasian plates. Here we used seismic data from a 30-station network deployed in the rupture area of the M6.4 earthquake, about one month after its occurrence. This station network covers an urban area, thus being subject to higher seismic-noise signals compared to northern Chile.

We numerically compared the prediction performance of DeepPhasePick in both tectonic regimes with the detections done by an

Figure 21. Estimation of time onset and associated uncertainty for predicted *P* (left-hand panel) and *S* (centre: *E* component, left: *N* component) phases of the event *e1* in Fig. 20. Results from applying MCD method to each seismogram component are shown as in Fig. 3. Pick statistics for this event are reported in Table S2.

in-house developed STA/LTA trigger algorithm applied to all vertical component waveforms. For this test, we used STA and LTA window lengths of 1.0 and 20.0 s; STA/LTA trigger and det trigger ratios of 8.0 and 1.5; and bandpass filter lower and upper corner frequencies of 2.0 and 10.0 Hz.

3.5.1 Performance in a lower-seismic noise region: northern Chile subduction zone

The cumulative number of *P* and *S* phases predicted by DeepPhasePick on data from one representative as well as all available stations in northern Chile, depict an abrupt increase right after the occurrence of the 2007 *M*7.7 Tocopilla main shock (Figs 17a and b) and the 2014 *M*8.1 Iquique main shock (Figs 18a and b), corresponding to the beginning of the aftershock series of these large megathrust earthquakes. Less pronounced increments in cumulative predictions are observed at other times as well: after a *M*7.1 aftershock occurring approximately one month following the Tocopilla main shock (Figs 17a and b), and after the occurrence of the largest foreshock (*M*6.7; 2014-03-16) and aftershock (*M*7.6; 2014-04-03) of the Iquique sequence (Figs 18a and b).

DeepPhasePick successfully captured a large majority of the various sized events occurring in the early post-seismic stage of the Tocopilla and Iquique main shocks (Figs 17c and 18c), which demonstrates the high resolution power of the algorithm. In particular, DeepPhasePick was capable of detecting *P* and *S* phases of several events occurring only a few minutes after the *M*7.6 aftershock in the Iquique earthquake sequence (Fig. 18c).

3.5.2 Performance in a higher-seismic noise region: Albania

For most of the stations in northern Chile, the cumulative number of *P* phases predicted by DeepPhasePick is comparable to the cumulative detections made by a classical STA/LTA algorithm (Figs S5 and S6), as one might expect from high-SNR seismic data. However, this does not hold true for several stations in Albania (Figs S7 and S8), which presumably recorded lower-SNR seismic data, though the overall cumulative number of predicted *P* phases and STA/LTA detections across all the stations in this region is still comparable (Fig. 19b).

The discrepancy between the cumulative STA/LTA detections and DeepPhasePick predictions in the Albanian data arises mostly in two

distinguishable scenarios. In the first scenario, cumulative STA/LTA detections greatly surpass *P*- and *S*-phase predictions (e.g. stations AB05, AB12, or AB21). Figs 19(c) and (d) illustrate one example of this, where the STA/LTA algorithm detects numerous false positives in the noisy one-hour waveform, whereas DeepPhasePick predicts only one *P*- and *S*-phase occurrence. In the second scenario, cumulative *P*-phase predictions are considerably higher than STA/LTA detections (e.g. stations AB10 or AB27, Figs S7 and S8). In this case, presumed false positive predicted by DeepPhasePick could be discarded, for instance, if they are not detected in a minimum number of stations when applying a phase associator algorithm.

In spite of eventual mispredictions generated due to noisy data, DeepPhasePick is generally able to detect multiple events across a station network. One example of multistation prediction is shown in Fig. 20, where six events are well detected in at least five stations within a 400-s window. Fig. 21 shows the corresponding time onsets for one of these events, generated by applying the MCD method in the picking stage. Similar results for two more events shown in Fig. 20 are presented in Figs S9 and S10. From the statistics of the picks predicted for the three events shown in Figs 21, S9 and S10, which are reported in Tables S2, S3 and S4, we observe that the difference between the preliminary phase time onsets (*tons_prelim*) obtained in the phase detection stage and the refined ones (*tons_pred*) computed in the picking stage can be up to 0.13 s for *P* phases and up to 0.17 s for *S* phases.

4 DISCUSSION

We have demonstrated that DeepPhasePick can be successfully applied to accurately detect and pick *P* and *S* phases originating from local earthquakes. The accurate predictions produced by DeepPhasePick result from the highly optimized set of hyperparameters defining its convolutional and recurrent deep neural networks trained for the tasks of seismic phase detection and picking, respectively. The systematic optimization process implemented aimed at compensating the limited seismic data used for training the models.

Results from the phase detection model optimization give us clues on the network architecture as well as input seismic samples characteristics that make the model perform more efficiently. First, the optimization indicates that the network detection capacity is enhanced by using a deeper block of convolutional layers. This can be explained by the fact that the model's ability to learn patterns from the input data, as well as the model's capacity to generalize so as to identify those patterns in new unseen data, are usually enhanced by adding convolutional layers to a CNN-based model. A large number of dense layers in the network, which aim at learning non-local relationships in the input data, does not seem to be required for improving network performance. Secondly, the network learns features in *P* and *S* phases more effectively when it is fed with relatively long input seismic windows which have not been filtered. Longer windows may ease the extraction of relevant seismic features in order to better discriminate between *P* and *S* phases and identify noise, particularly if very long-period background seismic noise is present. Interestingly, the network detects *P* phases better when sample windows contain a larger fraction of noise prior to a shorter portion of signal, in a way that resembles how analysts commonly identify this phase. Unlike *P* phases, optimized detection of *S* phases is obtained on sample windows consisting of a similar fraction of noise relative to signal, which may imply that the model learns patterns from features such as the *S* coda in order to recognize this phase.

Predictions performed on seismic samples from two independent test sets show that DeepPhasePick is capable of recognizing manually as well as automatically picked *P* and *S* phases with high accuracy, although it decreases for lower-quality automatic picks. These results also demonstrate that DeepPhasePick predicts phase time onsets which are comparable to those picked by analysts, as can be seen from the narrow time residual distributions in Figs 11(c) and 12(c). These residuals are comparable to those obtained in previous studies that implemented a deep learning-based picking approach (Ross *et al.* 2018a; Zhu & Beroza 2018), even though a much smaller data set was used for training DeepPhasePick.

In particular, we compared the performances of DeepPhasePick and the recently published attention mechanism-based EQTransformer model (Mousavi *et al.* 2020c) on two different test sets. The first test set includes all the 2853 correctly classified *P*- and *S*-phase samples from the phase detection evaluation (Fig. 7). The second test set is formed by a random selection of 1000 event samples (1000 *P*-phase and 1000 *S*-phase samples) taken from the STEAD test set (Mousavi *et al.* 2019a), on which EQTransformer was evaluated (Mousavi *et al.* 2020c). Since EQTransformer was trained using longer samples than DeepPhasePick, to perform this comparison we extended the samples in the first set by including additional seismic data taken from the corresponding sample traces. To ensure that the EQTransformer detection worked properly, samples in the STEAD test set were also extended by adding a 10-s noise window before and after each sample. These noise windows were formed by concatenating 10 times the first and the last second of the sample amplitudes, respectively. We performed the detection and picking applying DeepPhasePick and EQTransformer directly on the resulting MiniSeed samples. The resulting time residuals between the analyst phase time onsets and the predicted onsets from both methods are shown in Figs S11(c)–(f) for the first test set and Fig. S12 for the second test set. These results were obtained by applying EQTransformer using the best-performing parameters *detection_threshold* = 0.1, *P_threshold* = 0.1, *S_threshold* = 0.1, *overlap* = 0.9 and *batch_size* = 100 in the function *mseed_predictor* (as explained in <https://eqtransformer.readthedocs.io/>) and applying DeepPhasePick using probability trigger threshold of *pb_P_th1* = *pb_S_th1* = 0.90. In the first test set, *S*-phase time residuals are slightly more concentrated towards negative values for EQTransformer compared to DeepPhasePick. This time-shift is also observed for the *P*- and *S*-phase time residual distributions obtained by applying DeepPhasePick on the STEAD test set, although in the opposite direction. This divergence indicates that DeepPhasePick predicts earlier picks than EQTransformer, which may reflect the difference in the picking criterion applied by analysts who built both test sets. Alternatively, this could be related to the characteristics of the seismic signal that each model learns during the training. Reported metrics indicate that both models perform comparatively well on both test sets, with EQTransformer doing slightly better on the STEAD test set. This demonstrates that using a model with highly optimized hyperparameters, such as DeepPhasePick, is a good alternative approach when only a relatively small training data set is available.

Some degree of correlation was found between analyst pick classes and classes predicted by DeepPhasePick (see Fig. 13). We note here that phase-pick weighting made by analysts is not an exact measure, but usually based on experience and intuition. Hence we would not necessarily expect a perfect correlation, and the weighting provided by DeepPhasePick might in fact be more objective.

DeepPhasePick predicts *P*- and *S*-phase time onsets which are at least comparable to the time onsets obtained by applying dedicated

automatic picking algorithms such as *MPX* (Aldersons 2004; Di Stefano *et al.* 2006) and *Spicker* (Diehl *et al.* 2009), which served to derive the high resolution catalogues for the Northern Chile region shown in Fig. 14. Since DeepPhasePick also computes uncertainties and weights associated to the predicted picks, it can be used as a compelling alternative to those methods. However, DeepPhasePick is not restricted for use in the northern Chilean subduction zone, where the seismic samples used in training the models were originated. The algorithm is also able to predict P and S phases from local earthquakes occurring in a different tectonic regime, as we demonstrated for seismic data recorded by a 30-station network in a region in Albania (e.g. Fig. 20).

DeepPhasePick has been designed to internally share the knowledge learned from the optimization of the phase detection model to the phase picking models, allowing the algorithm to perform both tasks in a joint two-stage process. Consequently, DeepPhasePick can be applied directly on continuous seismic waveforms with minor pre-processing involved, so as to determine accurate P and S time arrivals that can then feed a phase associator algorithm in the next stage of an automatic earthquake location workflow. Even though the training and inference (Monte Carlo sampling) times of the LSTMs used in the picking stage are slow compared to the CNN used for phase detection, this is to some degree balanced by the fact that the LSTMs only pick the phases within short time windows that have been previously detected by the CNN. DeepPhasePick can also be used to only output the preliminary arrivals obtained from the detection stage, in case fast pick estimation is required. However pick uncertainties are only obtained from the picking stage. In this final stage the picks are substantially improved, as illustrated in Figs S11(a)–(d), which shows the results from applying DeepPhasePick on the correctly classified samples from the phase detection evaluation. We can see that, compared to the preliminary predicted P and S picks obtained in the detection stage (standard deviations of 0.14 and 0.23 s for P and S phases, respectively), the distributions of time residuals narrow after the picking stage (standard deviations of 0.11 and 0.21 s for P and S phases, respectively), indicating a significant reduction in the picking error after the second stage.

Further improvement of DeepPhasePick can be addressed in future work, for instance by retraining the CNN-based phase detection model with additional manually picked samples from a new region of interest. A simple way to achieve this upgrade would be to use the new data for applying techniques such as feature extraction and fine tuning on the optimized model here presented. Further, the RNN-based phase picking models can be retrained by using more than one shifted version of each available seismic record (see e.g. Ross *et al.* 2018a). This would provide a broader spectrum of learnable sequential data during the training, which might improve the picking models performance, though with the caveat that the computing time required to train the models would further increase.

5 CONCLUSION

The fast development in deep learning algorithms has made it possible to reach super-human performance levels in tasks involving huge amount of data, such as image classification and natural language processing. In this work, we leveraged this computational progress to develop DeepPhasePick, a novel two-stage algorithm for detection and picking of P and S seismic phases originating from local earthquakes. DeepPhasePick has been built based on highly optimized convolutional and recurrent deep neural network architectures trained for such tasks. In a first stage, DeepPhasePick

reports probabilities of waveform samples belonging to three phase classes (P, S or Noise). Preliminary phase onsets obtained from these probabilities are refined in a second step, in which final time onsets and their associated uncertainty are obtained by applying the Monte Carlo Dropout regularization technique, as an approximation of Bayesian variational inference.

DeepPhasePick has proven capable of recognizing both manually and automatically picked P and S seismic phases with high accuracy. It can also predict phase time onsets, which are comparable to those picked by analysts or derived from conventional, dedicated automatic phase picking algorithms. The P- and S-phase time onsets, as well as their associated uncertainties, predicted by DeepPhasePick from continuous seismic data can be directly used to feed a phase associator algorithm as part of an automatic earthquake location workflow.

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DATA AVAILABILITY

For training DeepPhasePick models for phase detection and picking tasks, we used waveform earthquake data collected from networks ZB (Schurr *et al.* 1999), ZE (Haberland *et al.* 1996), 8F (Wigger *et al.* 2016), Y9 (Fuenzalida *et al.* 2013), CX (GFZ German Research Centre for Geosciences & Institut des Sciences de l'Univers-Centre National de la Recherche CNRS-INSU 2006) and GE (GEOFON Data Centre 1993) accessed via EIDA web services (e.g. <https://geofon.gfz-potsdam.de/>).

For the evaluation of the performance of DeepPhasePick in independent test sets built from automatically derived earthquake catalogues, we used waveform earthquake data taken from networks CX, IQ (Cesca *et al.* 2009), 3D (Asch *et al.* 2014) and GE, as well as from Chilean Seismological Network (C, C1) stations (Barrientos 2018) accessed via IRIS webservices (<http://ds.iris.edu/SeismiQuery/>), the MEJIPE temporary network deployed by FU Berlin (Salazar *et al.* 2013) accessed via EIDA web services, and a temporary network deployed by the Chilean ONEMI, DGF, and CSN institutions accessed from CSN upon request.

The performance of DeepPhasePick predictions was further evaluated on continuous waveform data taken from networks CX and 9K (Schurr *et al.* 2020).

The optimized DeepPhasePick models trained for phase detection and phase picking tasks, together with an example script that applies DeepPhasePick method for both tasks on continuous waveforms, will be available via the GitHub repository <https://github.com/hsoptoparada/DeepPhasePick>.

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SUPPORTING INFORMATION

Supplementary data are available at [GJI](https://doi.org/10.1093/gji/227/2/1268) online.

Table S1. Precision, Recall and F1-score evaluation metrics at two probability thresholds in Fig. 7(b). Here $F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$

Table S2. Statistics of predicted picks shown in Fig. 21 for event e1 in Fig. 20.

Table S3. Statistics of predicted picks shown in Fig. S9 for event e7 in Fig. 20.

Table S4. Statistics of predicted picks shown in Fig. S10 for event e8 in Fig. 20.

Figure S1. (a–c) One representative earthquake waveform from Northern Chile, which contains the examples of predicted E, N, Z (east, north, vertical) sample windows shown in Fig. 3. Red and blue solid lines represent the predicted *P*- and *S*-phase time onsets obtained in the phase picking stage. (d) Predicted probability time-series for the Noise (N), *P*- and *S*-phase classes obtained from the phase detection stage. Predicted probabilities are assigned at the centre of the moving window with length defined by the optimized hyperparameter win size (see Section 2.5). (e) Predicted probability time-series for the *P*- and *S*-phase classes used in the picking stage. The *P*-phase time-series is shifted in time compared to the one in (d) due to the optimized hyperparameter value $frac_pre_P$ (0.7). The *S*-phase time-series is not shifted since $frac_pre_S$ is 0.5 (see Section 2.5). A grey dashed line indicates the probability threshold applied in the detection stage ($pb_P_th1 = pb_S_th1 = 0.90$). Predicted *P*- and *S*-phase time onsets are shown as in (a–c).

Figure S2. (a and b) Evolution of the training and validation accuracy (a) and loss function (b) over the training epochs of the optimized model trained for phase detection. (c–f) Evolution of the training and validation accuracy and loss function over the training epochs of the optimized model trained for *P*-phase (c and d) and *S*-phase (e and f) picking.

Figure S3. Examples of correctly predicted *P*- (a), *S*- (b) and *N*-class (c) samples in the test set of 4320 samples. Subplots are plotted the same way as in Fig. 8.

Figure S4. One example of *S* phase in the test set of 4320 samples, which was misclassified by the network as *P*-phase. Subplots are plotted the same way as in Fig. 8.

Figure S5. Cumulative number of *P* (red curve) and *S* (blue curve) phases predicted by DeepPhasePick ($pb_P_th1 = pb_S_th1 = 0.98$), and triggered detections by the STA/LTA algorithm (green curve) on continuous seismic data recorded by the stations with available data in northern Chile. Last subplot shows the combined results for all the stations in the network. Cumulative curves are plotted for the time interval between two months before and two months after the 2007 *M*7.7 Tocopilla main shock (magenta dashed line). An orange dashed line indicates the time of occurrence of a *M*7.1 aftershock (2007-12-16) ~50 km south of the main shock epicentre.

Figure S6. Cumulative number of *P* (red curve) and *S* (blue curve) phases predicted by DeepPhasePick ($pb_P_th1 = pb_S_th1 = 0.98$), and triggered detections by the STA/LTA algorithm (green curve) on continuous seismic data recorded by the stations with available data in northern Chile. Last subplot shows the combined results for all the stations in the network. Cumulative curves are plotted for the time interval between two months before and two months after the 2014 *M*8.1 Iquique main shock (magenta dashed line). Two additional orange dashed lines indicate the time of occurrence of the *M*6.7 foreshock (2014-03-16) and the *M*7.6 aftershock (2014-04-03) in the Iquique sequence.

Figure S7. Cumulative number of *P* (red curve) and *S* (blue curve) phases predicted by DeepPhasePick ($pb_P_th1 = pb_S_th1 = 0.98$), and triggered detections by the STA/LTA algorithm (green curve) on continuous seismic data recorded by the stations with available data in Albania. Cumulative curves are plotted for the time interval between 2019-12-19 and 2020-02-24, during the aftershock sequence of the 2019 *M*6.4 Albania earthquake. First 15 stations in the network are shown here.

Figure S8. Similar to Fig. S7, showing results from remaining stations in the Albanian network. Last subplot shows the combined results for all the stations in the network.

Figure S9. Similar to Fig. 21, for detected event e7 in Fig. 20. Pick statistics for this event are reported in Table S3.

Figure S10. Similar to Fig. 21, for detected event e8 in Fig. 20. Pick statistics for this event are reported in Table S4.

Figure S11. Results from the comparison of testing DeepPhasePick and EQTransformer models on the test set including all the correctly classified *P*- and *S*-phase samples (1430 *P*-phase and 1423 *S*-phase samples) from the phase detection evaluation in this work (Fig. 7). (a and b) Time residuals distribution for *P*- and *S*-phase samples (as in Figs 11c and 12c) obtained from the preliminary picks computed in the phase detection stage of DeepPhasePick. (c and d) Time residuals from the refined picks estimated after the phase picking stage of DeepPhasePick. (e and f) Time residuals obtained from applying EQTransformer model. Reported mean (μ), standard deviation (σ) and mean absolute error (MAE) are calculated on these residual distributions ($|tres| \leq 0.8$).

Figure S12. Results from the comparison of testing DeepPhasePick and EQTransformer models on 1000 randomly selected event samples (1000 *P*-phase and 1000 *S*-phase samples) from the STEAD test set. (a and b) Time residuals distribution for *P*- and *S*-phase samples (as in Figs 11c and 12c) obtained from the refined picks estimated after the phase picking stage of DeepPhasePick. (c and d) Time residuals obtained from applying EQTransformer model. Reported mean (μ), standard deviation (σ) and mean absolute error (MAE) are calculated on these residual distributions ($|tres| \leq 0.8$).

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