Predicting historical phonetic features using deep neural networks: A case study of the phonetic system of Proto-Indo-European

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Abstract

Traditional historical linguistics lacks the possibility to empirically assess its assumptions regarding the phonetic systems of past languages and language stages beyond traditional methods such as comparative tools to gain insights into phonetic features of sounds in proto- or ancestor languages. The paper at hand presents a computational method based on deep neural networks to predict phonetic features of historical sounds where the exact quality is unknown and to test the overall coherence of reconstructed historical phonetic features. The method utilizes the principles of coarticulation, local predictability and statistical phonological constraints to predict phonetic features by the features of their immediate phonetic environment. The validity of this method will be assessed using New High German phonetic data and its specific application to diachronic linguistics will be demonstrated in a case study of the phonetic system Proto-Indo-European.

1 Introduction

Since the beginning of historical linguistics, one of the main aims of historical phonology and phonetics has been to reveal phonetic features of now lost sounds and phonological systems of past languages. The study of the phonetic system of earlier stages of languages is a crucial prerequisite to uncover sound change and effects on sound change precisely. The methods, however, are limited for every language whose speakers cannot be invited to a phonetics lab for detailed testing. The temporal scope of inquiries into language change would be fairly limited if we could only examine language change as far back as voice recording and experimental testing methods were present. If we want to study language change over thousands of years, we must rely on robust techniques to approximate historical phonetic features as well as possible. The most prominent methods in historical linguistics so far to achieve this goal are based on comparative approaches (cf. Campbell, 2013; Beekes and Vaan, 2011; Meier-Brügger et al., 2010). Especially for the reconstruction of proto-languages, historical phonologists use the comparative method to estimate the approximate quality of sounds by investigating their outcomes and effects in the descendant languages. However, approaching historical phonetics by comparative means bears the disadvantage that the more the daughter languages disagree in certain respects, the less precise are the estimates scholars can make for the respective proto-sounds. For some problems for which comparative techniques yield imprecise results, there is a need for alternative methods to tackle these issues. Moreover, there is also no alternative method for cross-checking assumptions obtained through the traditional methods as such an alternative would need to operate on a basis different from diachronic comparison. Thus the method proposed in this paper makes use of synchronic structures and features of a language’s phonology and feeds this data into a deep neural network to predict the phonetic features of unknown sounds. The data the network can draw upon is the direct phonetic environment of each sound with the goal to predict its features only by the features of its environment.

The reason for the predictability of sound features in the context of their environment is due to coarticulatory effects, statistical constraints and local predictability. Coarticulation refers to the observation that sounds tend to both influence and be influenced by their environment phonetically (see e.g. Kühnert and Nolan, 1999; Ohala, 1993a; Hardcastle and Hewlett, 2006; Fowler, 1980). This reciprocal influence can be detected synchronically which makes it a possible alterna-
tive to be used for historical phonology if applied to historical language stages or proto-languages: In theory, sounds constantly influence their environment and are affected by it at the same time so that a tight net of interlaced dependencies between sounds and their environment arises. There are indications that sound changes which better fit into this phonetic structure in their initial stage are more likely to become widely adapted (Donegan and Nathan, 2015; Blevins, 2015; Ohala, 1993a,b; Hale, 2003). Similarly, and partially originating from coarticulatory processes, we find certain types of phonological constraints in languages, be it syllable composition constraints or the prevention of certain consonant clusters which make up a language’s phonotactics. These constraints can be both absolute and statistical, whereby absolute constraints are rules which are never violated, whereas statistical constraints constitute a strong dominance of one phonological shape over others. The network can utilize a language’s phonotactics, constraints and coarticulatory effects to predict the phonetic features of a target sound. Feature predictions from environmental properties have already been studied in quantitative phonetics and proven to be possible to some degree due to local predictability effects (see e.g. Priva, 2015; Van Son and Van Santen, 2005; Raymond et al., 2006).

It is important to keep in mind that local predictability on the basis of the phonetic environment is, in fact, not contradictory to the observation that different sounds can occur in the same environments which can be demonstrated using minimal pairs. Predictability in this context does not mean that a certain environment of a given sound always yields certain phonetic properties, it is rather a probabilistic observation that environments tend to occur paired with certain phonetic features and that this tendency of forming patterns is what can be predicted using probabilistic models and machine learning algorithms.

2 The deep neural network approach

Using machine learning algorithms is not new to the field of linguistics, though it is one of the more recent methods. While these approaches are found in an increasing number of studies in linguistics in general, in historical linguistics in particular the method is less used although some studies have been published in this or adjacent fields such as cladistics (Jäger et al., 2017; Jäger and Sofroniev, 2016). Since this approach of predicting sound features by the features in the phonetic environment only works synchronically, the deep neural network used for this needs to be trained on better known phonological features as the basis for predicting unknown features.

The data fed to the network must therefore contain a dataset where the phonetic environment serves as the input that is mapped on the target sound. To achieve this, the lexical corpus data needs to be split into trigrams or pentagrams of phonetic segments which are then categorized with regard to their phonetic features. Afterwards, the middle or target sound is removed and the remaining environment passed through the network with the respective target sound features as labels. Doing this trains the model to detect the correct phonetic features for the target sound given its environment. If the network has successfully trained, the environments of unknown sounds can be passed to the model which will, in turn, predict the features of the sounds on the basis of its weights and biases obtained in the training process. When the network performs well on the training data, we have little reason for it performing worse on the prediction of unknown sounds. Deep neural networks are especially suited for this task since other methods such as random forests or support vector machines have performed worse on this classification in preliminary tests I conducted beforehand. These three approaches, Deep neural networks, random forests and support vector machines, are entirely different approaches to machine learning classification tasks: While random forest classificators aim at finding the best decision tree by partitioning the data in subgroups, support vector machines establish the best splitting function, a hyperplane, to classify new samples according to their position in the multi-dimensional space. Deep neural networks on the other hand aim at optimizing the decision function through means of building abstract representation of the data and ‘learning’ the occurrence patterns of data features. It is not always possible to determine why some algorithms perform worse on some datasets and better on others. In the task at hand we can merely state that deep neural networks...
seem to find the global minimum, or a better local minimum, of the decision function well while other algorithms do not perform on the same level, presumably due to their characteristics not being ideal for this particular case. In the following section, a case study on Proto-Indo-European shall function as an example study that can be conducted using neural networks.

3 Case study: The phonetic system of Proto-Indo-European

The phonetic system of Proto-Indo-European (PIE) is an ideal field to demonstrate the capabilities of this neural network approach for several reasons: (1) while the phonetic inventory of PIE, along with its phonotactics, has been reasonably well investigated (Clackson, 2007, 64-71; Meier-Brügger et al., 2010, 272-275; Byrd, 2015; Ringe, 2017, 13-17; Fortson IV, 2011, 62-64), there are still unknown aspects that lead to scholarly discussions and diverging theories such as the Glottalic theory. (2) three sounds of PIE, the so-called laryngeals, are still a matter of debate since they are only scarcely attested in PIE’s daughter languages and sometimes only through their effects on neighbouring sounds. The case study will therefore aim to propose an attempt to predict the laryngeals and to uncover possible inconsistencies in the phonetic system of PIE.

3.1 The data

One of the best resources to obtain reconstructed word data that is already digital is the English version of Wiktionary. Its validity as a repository of data for linguistic inquiry has been assessed by multiple studies and many other studies have already used its database for linguistic inquiry (e.g. Chiarosc et al., 2013; Navarro et al., 2009; de Melo, 2015; Zesch et al., 2008; Meyer and Gurevych, 2012). Especially regarding reconstructed language data, Wiktionary has the decisive advantage that the reconstructions follow certain guidelines (see Wiktionary contributors) unlike data collected from various different traditional dictionaries.

For this study, I extracted all PIE reconstructions found in page headings from the English Wiktionary .xml dump on 20.10.2018. Such a dump file contains all English Wiktionary pages including page and edit histories. The lemmas that were extracted were subsequently split into segments of trigrams: preceding sound, target sound and following sound with a final trigram count of 7782. Where a trigram contained a root ending, ‘-‘ was used as following sound to encode the root ending, cases of word-final or word-initial were added as ‘zero’ in the preceding or following sound slot, respectively. Each sound was ultimately classified according to its place and manner of its articulation according to the reconstructed phonetic inventory of PIE most scholars agree on (e.g. Clackson, 2007, 34; Beekes and Vaan, 2011, 119; Ringe, 2017, 8) without considering the glottalic theory.

3.2 Approaches to verify the method

Before we are able to apply any machine learning techniques to the data, we need to establish whether coarticulatory and statistical constraint effects exist in PIE and that the method is actually feasible for predicting sound features in general. Although there have been studies suggesting the existence of such effects as mentioned above, a preliminary analysis needs to be conducted to demonstrate the data shows these effects and that a deep neural network can indeed ‘learn’ them and make correct predictions on the basis of the observed patterns. For this reason, I set up a generalized linear logistic regression model as an example to determine the phonetic effects on the occurrence of the feature aspirated in PIE. The model was fit for best AIC through both top-down and bottom-up fitting. Before fitting, aliases were removed as

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2See Byrd (2015); Beekes and Vaan (2011); Clackson (2007) for a comprehensive overview of the scientific debate.
3https://en.wiktionary.org, accessed: 2019-03-13

4For the full list of features used in this study, please refer to the appendix.
well as collinear predictors up to a cutoff-point of Variance Inflation Factor (VIF) greater than 4.

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|----------|
| Intercept | -2.302     | 0.991   | -25.312  | 0.000    |
| labial preceding | -1.504     | 0.240   | -6.263   | 0.000    |
| sibilant preceding | -2.310     | 0.587   | -3.939   | 0.000    |
| liquid preceding | -0.843     | 0.245   | -3.446   | 0.000    |
| syllabic cons. preceding | 1.137     | 0.380   | 2.994    | 0.003    |
| back vowel preceding | -1.131     | 0.267   | -4.232   | 0.000    |
| mid vowel preceding | -1.022     | 0.178   | -5.730   | 0.000    |
| close vowel preceding | -0.947     | 0.468   | -2.021   | 0.043    |
| h3 preceding | 1.519      | 0.518   | 2.933    | 0.004    |
| h2 preceding | -2.106     | 0.513   | -4.103   | 0.000    |
| h2 preceding | -1.185     | 0.598   | -1.981   | 0.048    |
| word boundary following | 1.439     | 0.154   | 9.336    | 0.000    |
| voiceless cons. following | -2.279     | 0.390   | -5.848   | 0.000    |
| nasal following | -1.691     | 0.512   | -3.304   | 0.001    |
| liquid following | 0.444      | 0.175   | 2.543    | 0.011    |
| syllabic cons. following | 0.381     | 0.185   | 2.055    | 0.040    |
| velar following | 1.487      | 0.509   | 2.919    | 0.004    |
| back vowel following | 0.526      | 0.170   | 3.091    | 0.002    |
| plosive following | -1.041     | 0.415   | -2.510   | 0.012    |
| h2 following | -2.494     | 1.006   | -2.481   | 0.013    |

Table 1: Generalized linear logistic regression for the occurrence of the feature *aspirated*.

It can be observed in table 1 that several predictors were significant. E.g. preceding sibilant reduces the probability of the target sound being *aspirated* whereas following velar increases this probability. As suggested by this model, the data contains information on coarticulatory and statistical constraint effects the neural network can draw upon.

As a second approach to ensure that the presented method and data is suitable for predicting sound features, I conducted a preliminary study using the same method to predict the features of New High German sounds. For this analysis, I utilized the German phonology lemma data from CELEX2 (Baayen et al., 1995) in the syllabified phonetic lemma transcription with stress in the DISC character set (*PhonStrsDISC*). After extraction from the CELEX2 file, the data were prepared using the same process as for the PIE data with a final sample size of 441236 German trigrams. The method was simultaneously tested with a dataset in which each lemma was oversampled proportional to its frequency of occurrence in the ‘Mannheimer Korpus’ provided by CELEX2 (*Mann_Freq*) (see Gulikers et al., 1995). While this approach would ideally proportion the dataset more realistically and could, in theory, improve model training, it did not enhance the performance of the network and was therefore discarded.

Each sound of those trigrams was classified according to 38 phonetic features (e.g. *consonant, nasal, plosive*) where 0 and 1 indicate the absence/presence of a particular feature, respectively. Note, that these 38 features contain some redundancies (e.g. *vowels* are entirely contained in the feature *continuant*). This is due to the fact that a deep neural network performs best on as many input features as possible since there might be some relevant signal in a seemingly redundant or unimportant feature vector. Accordingly, specifying two complementary features like e.g. *voiced* and *voiceless* can increase the network’s performance since the two categories only apply to consonants. Otherwise, a single binary feature [+voice] would not only encode voiced consonants but also all vowels and therefore decrease the ability of the network to detect voiced consonants specifically. Redundancy itself is also not a problem as redundant or irrelevant information in the data is weighted less important during training while the network focuses on those features that have predictive power.

Also, only basic features (13 features in total for consonants and 10 features for vowels) such as e.g. *consonant, velar* and *labial* were used as target features for the prediction of German sound features. The reason for this decision was that the more fine-grained the distinctions become, the fewer occurrences of the feature there are on which the network can train. Therefore, although the feature *liquid* containing German *r* and *l* was further divided into *rhotic* and *lateral* as features contained in the classification of the phonetic environments, only *liquid* was tested as a target feature. If *rhotic* were tested as target feature on a sound with unknown features, the network would train only on the sound *r* and therefore not necessarily train on the feature *rhotic* but rather learn to discriminate *r* from all other sounds which has in turn little explanatory power when predicting the *rhotic* feature for other sounds.

The method was tested on the German sounds *p, r, v, a*: as an arbitrary preliminary selection that ideally is representative of all other sounds in the New High German phonetic inventory. Therefore, four datasets were prepared, where the respective sound was removed as target sound and its presence in any phonetic environment was indicated by adding a new feature only for this sound. For example when the phonetic environment in a par-
ticular trigram contained \( r \) while \( r \) was the sound to be later predicted by the network, \( r \) was classified in a dummy feature category that only encodes presence/absence of this particular sound. This procedure is necessary since removing all instances of the particular sound, \( r \) in this case, in the phonetic environment would reduce the number of environments and therefore distort the data.

After data preparation, a single network was set up for each feature and trained one feature at a time with a binary output to predict the presence or absence of the feature. I.e. this binary network was trained to detect a particular feature and to predict its presence or absence for unseen sound environment data. After the entire data were shuffled and the test and validation data were separated from the training sets using the Stratified ShuffleSplit cross-validator included in the python package scikit-learn (Pedregosa et al., 2011), the training sets were over-sampled before each run to counter class imbalance with the SMOTE algorithm (Chawla et al., 2002) implemented in the ‘Imbalanced-learn’ (Lemaître et al., 2017) python package. The network was trained for 30 epochs using the optimizer Adam with a learning rate of 0.01 with a batch size of 250 samples with the layer configuration displayed in table 2.

| Layer          | Layer size | Activation |
|----------------|------------|------------|
| Dense layer 1  | 256        | ReLU       |
| Dense layer 2  | 128        | ReLU       |
| Dense layer 3  | 64         | ReLU       |
| Dense layer 4  | 32         | ReLU       |
| Output layer   | 2          | softmax    |

Table 2: Network architecture for the German feature prediction task

For the subsequent evaluation of the model performance, weights and biases were used form the epoch at which the network performed best on the validation data during training using the Keras callback ModelCheckpoint (Chollet et al., 2015). This procedure minimizes the risk of the model being stuck at a local minimum in the search space at the time training stops after an arbitrarily chosen number of epochs. It has been established in preliminary tests that the model performance was enhanced when training on an all-consonant or all-vowel subset of the data: First, a model was trained to predict the feature [± consonant] and after the prediction, the main model was trained on consonant or vowel data according to the prediction of the preliminary model. After each training, the network performance was evaluated and subsequently tasked with predicting the particular feature for the respective test sound. The results are presented in tables 3, 4, 5, and 6 which show which number of samples in the test sets were classified correctly or incorrectly. I.e. 24656 consonant samples in the column \( TP \) means that 24656 samples of all positive samples in the test set were correctly classified as positive. Similarly, in table 3 in the first row, 7211 samples in prediction: feature present denote that 7211 of all tested instances of \( p \) were classified as [+consonant].

Note that model accuracy metrics such as F1 score, precision, or recall are not given here since these measures only evaluate a classifier’s performance on a mixed dataset. Because the method proposed here aims at performing well on determining whether a sound shows a given feature and since this feature is either present in all samples of this sound or absent in all samples, the main goal is that the deep network yields more true positives than false negatives and more true negatives than false positives. Applied to the example in table 3 this means that since German \( p \) is [+consonant], ideally the majority of classified samples will be classified as such. If after model evaluation the number of false negatives were higher than the number of true positives, the model would likely not be able to classify the majority of samples correctly. More samples would end up being incorrectly labeled as negatives as a result of the poor model training yielding more false negatives than true positives. Therefore, a high false positive or false negative count is not a concern in itself as long as the ratio of true positives to false negatives and true negatives to false positives is always in favor of true positives or true negatives, respectively.

| Feature          | \( TP \) | \( FN \) | \( FP \) | \( TN \) | Pred. feat. present | Pred. feat. absent |
|------------------|---------|---------|---------|---------|---------------------|-------------------|
| consonant         | 24656   | 2184    | 850     | 15541   | 7211                | 1652              |
| nasal            | 3865    | 1553    | 4255    | 17148   | 2609                | 6229              |
| glottal          | 5471    | 1994    | 4341    | 15099   | 4860                | 3978              |
| affricate        | 732     | 172     | 6750    | 19187   | 2352                | 6486              |
| fricative        | 7156    | 802     | 4272    | 11786   | 2394                | 6444              |
| liquid           | 4698    | 1615    | 5361    | 15167   | 1670                | 7168              |
| sibilant         | 2148    | 1072    | 5670    | 17945   | 1634                | 7204              |
| voiced           | 11509   | 1081    | 3442    | 1158    | 582                 | 5256              |
| labial           | 3447    | 864     | 7656    | 14874   | 5907                | 3331              |
| dental/velarular | 8749    | 4993    | 8334    | 10167   | 4355                | 4683              |
| palatal          | 1016    | 270     | 4497    | 21055   | 2375                | 6465              |
| velar/velarular  | 4896    | 3035    | 4200    | 14710   | 1972                | 6866              |
| glottal          | 428     | 43      | 5481    | 20800   | 1858                | 6992              |

Table 3: Network evaluations and predictions for German \( p \)

The results show that all 13 tested features of \( p \) are predicted correctly, \( r \) is correctly predicted to be a voiced liquid, yet regarding place of articulation, which in German r-allophones is ranging
Table 4: Network evaluations and predictions for German r:

| Feature | TP | TN | TP | TN | Pred: feat. present | Pred: feat. absent |
|---------|----|----|----|----|---------------------|-------------------|
| consonant | 28908 | 11401 | 11039 | 5777 | 34673 | 10732 |
| nasal | 3722 | 1716 | 2702 | 1585 | 16238 | 23755 |
| plausive | 5524 | 2763 | 3882 | 12374 | 633 | 33658 |
| affricate | 732 | 172 | 6539 | 16482 | 7972 | 32019 |
| fricative | 4081 | 1903 | 4114 | 12027 | 11352 | 28639 |
| liquid | 1640 | 710 | 5259 | 16512 | 22042 | 17049 |
| sibilant | 2172 | 1048 | 4683 | 15822 | 8997 | 30994 |
| voiced | 8086 | 3236 | 3568 | 8913 | 30668 | 9023 |
| labial | 3907 | 1288 | 6205 | 12325 | 12071 | 27920 |
| dental/alveolar | 8974 | 3865 | 2844 | 8042 | 28021 | 11970 |
| palatal | 1056 | 283 | 3138 | 21098 | 3895 | 36096 |
| velar/uvular | 2916 | 1015 | 4037 | 14857 | 11004 | 28087 |
| glottal | 432 | 39 | 4728 | 18526 | 8695 | 31296 |

Table 5: Network evaluations and predictions for German a:

| Feature | TP | TN | TP | TN | Pred: feat. present | Pred: feat. absent |
|---------|----|----|----|----|---------------------|-------------------|
| consonant | 2584 | 1840 | 1111 | 15105 | 204 | 1638 |
| front vowel | 3658 | 1963 | 2714 | 7861 | 589 | 1253 |
| central vowel | 4546 | 1667 | 2529 | 7474 | 858 | 984 |
| back vowel | 1920 | 1032 | 3391 | 9873 | 831 | 1011 |
| round | 1395 | 653 | 3845 | 10123 | 898 | 944 |
| close | 3054 | 2729 | 2132 | 9301 | 493 | 1349 |
| mid | 5790 | 1670 | 2525 | 6231 | 595 | 1257 |
| open | 1281 | 3130 | 9133 | 1239 | 623 | 1378 |
| diphthong | 1097 | 3377 | 2776 | 12010 | 464 | 1378 |
| long | 6595 | 1544 | 2365 | 5712 | 1248 | 594 |

Table 6: Network architecture for the feature aspirated PI:

| Layer | Layer size | Activation |
|-------|------------|------------|
| Dense layer 1 | 128 | ReLU |
| Dropout layer 1 | 0.25 dropout rate |
| Dense layer 2 | 64 | ReLU |
| Dropout layer 2 | 0.25 dropout rate |
| Dense layer 3 | 32 | ReLU |
| Output layer | - | softmax |

Table 7: Network architecture for the feature aspirated PI:

The deep learning method applied to Proto-Indo-European

To prepare the PIE data for training, the data were randomly shuffled and split into training and test sets using the Stratified ShuffleSplit cross-validator included in the python package scikit-learn (Pedregosa et al., 2011). Afterwards, the training set was first oversampled with the SMOTE algorithm and subsequently under-sampled by removing Tomek links using SMOTE-Tomek (Batista et al., 2003) implemented in the ‘imbalanced-learn’ (Lemaître et al., 2017) python package to counter class imbalance in the dataset. Yet the SMOTE over-sampling process performed on the minority group increases the dataset’s variation, so to cope with this variation and to make sure that findings were not due to random biases during oversampling or stratification, I ran each network 100 times to have a representative number of slightly varying model outputs. Each of these runs yields a confusion matrix with the count of true positive, false negative, false positive and true negative predictions of the test samples. To determine whether the model performs significantly better than expected by a random class assignment, all confusion matrices were compared using Wilcoxon signed rank tests with continuity correction. For each model, I performed this test on the output of the 100 runs of true positives vs. false negatives to determine whether the network can clearly find a present feature and a second test on the 100 runs of false positives vs. true negatives to determine whether the network can clearly find the absence of a feature. When the Wilcoxon signed rank test is significant, the tested groups are ‘non-identical’ populations.

3.4 Example 1: The phonetic quality of the PIE laryngeals

In the following stage, a deep neural network can be set up to learn to detect the feature aspirated and to subsequently predict whether the laryngeals had this feature.

The network was trained for 50 epochs using the optimizer Adam with a learning rate of 0.01 and a batch size of 64 samples with the layer configuration displayed in table 7.

The dropout layers in this network architecture were implemented to reduce the effect of over-fitting due to the limited amount of training samples. Analogous to the training on the mod-
ern German dataset above, only weights and biases form the epoch at which the network performed best on the validation data during training were used. As mentioned above, the network was trained and evaluated 100 times in order to further minimize the effect of accidental findings in single runs. The results are listed in table 8 which is a summary of all test set prediction confusion matrices obtained in the 100 runs.6

|          | Positives | True positives | Negatives | False negatives |
|----------|-----------|----------------|-----------|----------------|
| Mean     | 58.32     | 213.3          | 602.5     | 104             |
| Median   | 58        | 213.5          | 601.0     | 104             |
| Std. dev.| 2.044     | 62.6           | 692.0     | 9.970           |

Table 8: Statistics of the confusion matrices from 100 runs for classifying the feature aspirated

Subsequently, a Wilcoxon signed rank tests with continuity correction with the alternative hypothesis H1: True positives greater than false negatives gives W = 10000.00 p < 0.00001. A second Wilcoxon signed rank tests with continuity correction with the alternative hypothesis H1: True negatives greater than false positives gives W = 10000.00 p < 0.00001. These test statistics show that in these 100 runs, the network was able to detect the feature aspirated reliably and, most importantly, when presented with an unseen dataset which either contains sounds that have the feature aspirated or sounds that do not, the network will correctly identify over 70 percent of the samples. The variance in the prediction accuracy in table 8 can be explained by, as previously addressed, noise in the data and variation in the partitioning and subsequent oversampling of the training set. Having established the functioning network, the model can be used to predict the target feature for sounds with unknown qualities. Since the laryngeals cannot be assigned a phonetic value by means of the comparative method, their properties can be predicted. To achieve this, the phonetic environment was passed through the networks after training at the end of each of the 100 runs. The output of every prediction is a classification matrix for each of the three laryngeals. Table 9 shows the test results. The networks trained on detecting the feature aspirated clearly predict the aspirated feature for h1. For h2, the model clearly rejects the feature aspirated. In the case of h3, the statistical tests indicate that the laryngeal possessed the feature aspirated, however because of the thin difference in the number of predicted samples, we still need to treat this finding with caution, since the feature is not as clearly predicted for h3 as it is for h1. It is likely that the aspiration present in h3 is weaker than or different from that of h1.

### 3.5 Example 2: The internal coherence of PIE nasals

Besides predicting phonetic features of unknown sounds, the deep neural networks can moreover detect inconsistencies or idiosyncrasies in PIE. One such example is the feature nasal which is present in both PIE non-syllabic (*m, *n) and syllabic nasals (*m, *n). While both are regarded to be phonetically identical and only differing in their syllability (Clackson, 2007, 35), an investigation using the deep neural network approach gives some insights into their relationship to one another: To analyze this feature, a deep neural network was set up with the architecture displayed in table 11.

| Layer       | Layer size | Activation |
|-------------|------------|------------|
| Dense layer 1 | 128        | ReLU       |
| Dropout layer 1 | 0.25 dropout rate   |       |
| Dense layer 2  | 64         | ReLU       |
| Dropout layer 2 | 0.2 dropout rate    |       |
| Dense layer 3  | 32         | ReLU       |
| Output layer   | 2          | softmax    |

Table 11: Network architecture for the feature nasal
used in 3.4. The resulting confusion matrices obtained after each evaluation of the 100 training runs are summarized in table 12.

| True positives | False negatives | False positives | True negatives |
|----------------|-----------------|-----------------|---------------|
| Mean           | 48              | 55              | 118.5         |
| Median         | 48              | 55              | 678.5         |
| Std. dev.      | 6.689           | 38.951          |               |

Table 12: Statistics of the confusion matrices from 100 runs for classifying the feature nasal

As this summary shows, the neural network had more difficulties learning the properties of nasal than it had learning the feature aspirated. The classifier only detects the feature less than 50 percent of the time it is presented with nasal sounds, which is approximately what could be expected by randomly classifying the rest samples. Moreover, a Wilcoxon signed rank test with continuity correction with the alternative hypothesis $H_1$: True positives greater than false negatives gives $W = 3144, p = 1$. As a result, it was not possible to successfully train the network on this feature. Given the large discrepancy in performance between this and the previous network and the fact that both models were optimized using the same methods, the problem must be data inherent. This finding raises the question of why exactly this series differs from the other features. This leaves three possible explanations: (1) The data containing the nasals is noisier compared to the other phonetic features so that the classifier cannot train on a consistent set of properties. Although data can be varying degrees of noisy, it is unlikely that this feature is overly affected by noise. (2) The nasal feature was weakly articulated in PIE and thus it had little effect on its environment. An effect so small that it did not leave stable traces the classifier could detect. (3) The third explanation is that the nasal series does not possess internal coherence. This reason is arguably the most probable given that the nasals consist of two different sets of nasals that contrast in their syllabicity, especially since syllabic and non-syllabic resonants are also allophones and are therefore in complementary distribution (cf. Schindler, 1977). Yet since the model was trained on detecting nasality – not syllabicity – while there were other syllabic consonants in the non-nasal group, it is also possible that the model is not solely misled by the difference in syllabicity and their complementary distribution. There might also be a difference in nasality itself which results in the feature not forming a consistent, classifiable group. In other words, the syllabic and non-syllabic nasals might additionally have also differed in their nasality (i.e. nasality being differently articulated in both cases), yet this observation needs to be further investigated before one can make more substantiated claims.

4 Conclusion

As has been demonstrated in this paper, using deep neural networks in historical phonetics is a viable method to predict unknown features and to uncover previously unnoticed inconsistencies within a language’s phonetic system. The tool is specifically powerful for historical linguistics since it does not rely on diachronic methods such as the comparative method to analyze and determine phonetic features but can draw upon synchronic phonetic patterns arising from coarticulation and statistical constraints. The results obtained through the machine learning technique presented in this paper are moreover reproducible and empirical, and can therefore be seen as complementary to previous results obtained by other empirical approaches such as the comparative method. However, the specific strengths and weaknesses of this method need to be further investigated in future research.

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Table 13: Phonetic feature assignment of each considered New High German sound

| Feature | Assignment |
|---------|------------|
| word boundary | zero |
| nasal | m, n, ñ |
| plosive | p, t, d, k, g, b |
| affricate | tf, ts, sf, x/c, h |
| fricative | f, v, s, z, j, ñ, x/c, h |
| liquid | l, r |
| rhotic | r |
| lateral | l |
| sibilant | s, z, ñ, ñ |
| voiced | m, n, ñ, d, g, j, v, l, r, z, b |
| voiceless | p, t, k, pf, tf, f, s, x/c, h |
| labial | m, p, f, v, b |
| bilabial | m, p, b |
| labiodental | pf, f, v |
| dental/alveolar | n, t, d, ts, s, z, l, r |
| palatal | j, ñ, f, r |
| velar/uvular | ñ, k, g, x/c, r |
| glottal | h |
| obstruent | p, b, t, d, k, g, pf, ts, tf, f, v, s, z, j, ñ, x/c, h, r |
| sonorant | m, n, ñ, i, i, ñ, e, y, ñ, ñ, ó, õ, ù, u, o, ò, ñ, a, ñ, u, ñ, o, õ, ñ, ñ, ñ, ñ, ó |
| occlusive | p, b, t, d, k, g, m, n, ñ, pf, ts, tf |
| continuant | f, v, s, z, j, ñ, x/c, h, r, i, i, ñ, e, ñ, ñ, ñ, y, ñ, ñ, ó, õ, ù, ñ, ñ, a, ñ, u, ñ, o, ñ, ó |
| consonant | m, n, ñ, d, g, j, v, l, r, b, p, t, k, pf, tf, j, s, z, f, x/c, h |
| front vowel | i, i, ñ, e, y, ñ, ó, õ, ù, ñ |
| central vowel | ñ, ñ, ñ |
| back vowel | u, ñ, ñ, ñ |
| close | i, i, ñ, e, y, ñ |
| mid | ñ, ñ, ñ, ó, õ, ù, ñ, ñ, ñ |
| open | ñ, ñ |
| diphthong | ai, ñ, ñ |
| open diphthong | ai, ñ |
| mid diphthong | au |
| front diphthong | ai, ñ |
| back diphthong | ñ, ñ |
| round | ñ, ñ, ñ, ñ, ñ |
| unround | i, i, ñ, e, ñ, ñ, ñ, ñ, ñ, ñ |
| long | ñ, ñ, ñ, ñ, ñ, ñ, ñ, ñ, ñ |
| short | i, i, ñ, ñ, ñ, ñ, ñ |

A Appendices

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| root ending | *<br>word boundary final/initial | zero |<br>voiced |<br>*b<sup>h</sup>, *d<sup>h</sup>, *g<sup>h</sup>, *g<sup>wh</sup>, *b, *d<sup>h</sup>, *g<sup>wh</sup>, *m, *m<sup>n</sup>, *n, *r, *l, *l<sup>n</sup>, *y, *w |<br>voiceless |<br>*p, *t, *s, *k, *k<sup>h</sup> |<br>nasal |<br>*m<sup>n</sup>, *m<sup>n</sup><br>|<br>aspirated |<br>*b<sup>h</sup>, *d<sup>h</sup>, *g<sup>h</sup>, *g<sup>wh</sup> |<br>labial/labialized |<br>*m, *p, *b, *s<sup>b</sup>, *w, *k<sup>h</sup>, *g<sup>wh</sup>, *g<sup>wh</sup> |<br>sibilant |<br>*s |<br>liquid |<br>*r, *l, *l<sup>n</sup>, *l<sup>n</sup> |<br>syllabic |<br>*r, *l, *m<sup>n</sup>, *t, *w, *u, *ü |<br>coronal |<br>*n, *n<sup>n</sup>, *t, *d, *d<sup>h</sup>, *s, *r, *l, *l<sup>n</sup>, *r<sup>n</sup>, *y, *w, *p, *t, *s<sup>b</sup>, *k<sup>h</sup>, *k<sup>wh</sup>, *k<sup>wh</sup> |<br>postvelar |<br>*k, *g<sup>h</sup>, *g<sup>wh</sup>, *g<sup>wh</sup> |<br>velar |<br>*k, *g<sup>h</sup> |<br>palatal |<br>*y |<br>front vowel |<br>*e, *ê, *i |<br>back vowel |<br>*o, *ô, *u, *ü |<br>center vowel |<br>*a, *â |<br>short vowel |<br>*e, *o, *a, *i |<br>long vowel |<br>*ê, *ô, *û, *â |<br>open vowel |<br>*a, *â |<br>close vowel |<br>*u, *û, *i |<br>laryngeal 1 |<br>*h<sub>1</sub> |<br>laryngeal 2 |<br>*h<sub>2</sub> |<br>laryngeal 3 |<br>*h<sub>3</sub> |<br>unspecified laryngeal |<br>*H |<br>consonant |<br>*b<sup>h</sup>, *d<sup>h</sup>, *g<sup>h</sup>, *g<sup>wh</sup>, *b, *d, *g, *g<sup>wh</sup>, *m, *m<sup>n</sup>, *n, *r, *l, *l<sup>n</sup>, *y, *w, *p, *t, *s, *k, *k<sup>h</sup> |<br>back consonant |<br>*k, *g<sup>h</sup>, *g<sup>wh</sup>, *g<sup>wh</sup>, *g<sup>wh</sup>, *k<sup>h</sup> |<br>front consonant |<br>*m, *m<sup>n</sup>, *p, *b<sub>b</sub>, *s<sup>b</sup>, *w, *s<sup>n</sup>, *r, *l, *n<sup>n</sup>, *t, *d, *d<sup>h</sup> |<br>stop |<br>*k<sup>h</sup>, *b, *s<sup>b</sup>, *p, *g<sup>h</sup>, *g<sup>wh</sup>, *k, *g<sup>wh</sup>, *k<sup>h</sup> |<br>obstruent |<br>*k, *p, *b<sub>b</sub>, *s<sup>b</sup>, *g<sup>h</sup>, *g<sup>wh</sup>, *k, *g<sup>wh</sup>, *k<sup>h</sup> |<br>sonorant |<br>*m, *m<sup>n</sup>, *n, *r, *t, *r, *y, *w, *e, *o, *u, *a, *i, *ê, *ô, *û, *â |<br>occlusive |<br>*k, *p, *b, *s<sup>b</sup>, *g<sup>h</sup>, *g<sup>wh</sup>, *k<sup>h</sup> |<br>continuant |<br>*s, *y, *w, *e, *o, *u, *a, *i, *ê, *ô, *û, *â |<br>Table 14: Phonetic feature assignment of each considered PIE sound |