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Improving Peptide Identification by Considering Ordered Amino Acid Usage

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IMPROVING PEPTIDE IDENTIFICATION BY CONSIDERING ORDERED AMINO
ACID USAGE

by

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ABSTRACT

Proteomics has made major progress in recent years after the sequencing of the genomes of a substantial number of organisms. A typical method for identifying peptides uses a database of peptides identified using tandem mass spectrometry (MS/MS). The profile of accurate mass and elution time (AMT) for peptides that need to be identified will be compared with this database. Restricting the search to those peptides detectable by MS will reduce processing time and more importantly increase accuracy. In addition, there are significant impacts for clinical studies. Proteotypic peptides are those peptides in a protein sequence that are most likely to be confidently observed by current MS-based proteomics methods. There has been rapid improvement in the prediction of proteotypic peptides for AMT studies based on amino acid properties such as amino acid content, polarity, charge and hydrophobicity using a support vector machine (SVM) classification approach. Our goal is to improve proteotypic peptide prediction. We describe the development of a classifier that considers amino acid usage that has achieved a classification sensitivity of 90% and specificity 81% on the *Yersinia pestis* proteome (using 3-AAU). Using Ordered Amino Acid Usage (AAU) feature, we were able to identify a different set of peptides that was not identified by the 35 peptides features that STEP (Webb-Robertson, 2010)[2] have used. This means that Ordered Amino Acid Usage (AAU) feature could complement other features used by STEP to improve identification accuracy. Building on this success, we used STEP (Webb-Robertson,

2010)[2] 35 amino acids features to complement Ordered Amino Acid Usage (AAU) feature in order to enhance the overall accuracy.

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LIST OF ABBREVIATIONS

AAU	Amino Acid usage
AUC	Area under curve
LDA	Linear Discriminant Analysis
MS	Mass spectrometry
PCA.....	Principal Component analysis
ROC	Receiver operating characteristic
SVM.....	Support vector machine

CHAPTER 1

INTRODUCTION

1.1 Problem and Hypothesis

Proteomics aim to identify and quantify all of the proteins present in a cell at a specific moment. Such studies typically pose challenges owing to the high degree of complexity of cellular proteomes and the low abundance of many of the proteins, which necessitates highly sensitive analytical techniques. Mass spectrometry (MS) has increasingly become the method of choice for analysis of complex protein samples. MS-based proteomics is a discipline made possible by the availability of gene and genome sequence databases and technical and conceptual advances in many areas, most notably the discovery and development of protein ionization methods, as recognized by the 2002 Nobel prize in chemistry (2003) [15]. Although Mass spectrometry (MS) offers a high-throughput approach to quantifying the proteome and therefore becomes the standard method of proteomic analyses, however, a lot of computation is required to analyze those large data STEP (Webb-Robertson, 2010)[2].

The first formulation of the peptides detectability problem was in 2006 (Tang, 2006) [1]. Since then, several algorithmic approaches have been proposed. Those approaches use different machine learning techniques and all share common steps:

- 1) Extract training data that is divided into positive and negative groups.

2) Use machine learning techniques on the training data to create a model for prediction.

Researchers have taken different approach to define the concept of prototypic peptides. For example STEPP (Webb-Robertson, 2010) [2] defines prototypic peptides to be those that have been included in the AMT database every time the parent protein is observed. In contrast, PeptideSieve (Mallick, 2007) [3] and CONSeQuence (Eyers, 2011) [4] use peptides that have been observed in 50% of all identification of the corresponding protein in a set of experiments. In this paper we used one of the three training testing dataset used by STEPP (Webb-Robertson, 2010) [2] and adopt that definition of prototypic peptides.

Researchers have used different features and different methods. For example STEPP (Webb-Robertson, 2010) [2] uses 35 peptide features as input to the support vector machine (SVM). PeptideSieve (Mallick, 2007) [3] uses 494 properties with Gaussian mixture likelihood scoring function. Also, authors used different methods, for example, ESPPredictor (Fusaro, 2009) [5] uses random Forests classification. While others used neural networks to classify peptides, such as Tang, et al. (Tang, 2006) [1].

In tandem MS experiments only a small number of peptides present can be reliably identified. Presumably, those peptides that cannot be reliably detected do not fragment appropriately for the spectrometer. We hypothesize that bonds between adjacent amino acids are an important factor affecting how a peptide fragments. Consequently, we propose to use an abstract model of bonds between adjacent amino acids as an additional feature for identifying proteotypic and non-proteotypic peptides computationally.

We refer to this feature as Ordered Amino Acid Usage (AAU). Specifically, we implicitly model peptide bonds at an abstract level by looking at ordered adjacent amino acids. To be clear, we do not explicitly model peptide bonds. Ordered amino acids tuples capture the mutual information of these peptide fragments at an abstract level. We have considered ordered adjacent amino acids (2-AAU) as well as ordered triples of adjacent amino acids (3-AAU). In this research, we have used the 35 features that STEPP have used, in addition to the new AAU feature.

1.2 Importance of topic

Several mass spectrometry-based quantitative proteomics methods attempt to comprehensively identify and quantify constituent proteins in complex mixtures.

Differences in the abundance of proteins in distinct samples have enabled scientist to

- Identify cellular functions and pathways affected by perturbations and disease.
- Revealed new components and changes in the compositions of protein complexes and organelles.
- Enabled detection of putative disease biomarkers (Mallick, 2007) [6].

A standard method for identifying peptides uses databases of peptides identified using tandem mass spectrometry (MS/MS). A unique advantage for identifying proteotypic peptides for accurate mass and elution time (AMT) studies is that the prediction of the detectable peptides along with accurate elution time prediction of these peptides would allow for prediction via computer simulation of an AMT database (database of peptides previously identified from tandem mass spectrometry [MS/MS] studies) without the costly and time consuming prior identification of peptides by

MS/MS. As a result, accurate prediction of proteotypic peptides for these studies could significantly reduce cost and time (Webb-Robertson, 2010) [2].

Different researchers have used different parameters and algorithms to calculate prediction of identified and unidentified peptides. For example, STEPP (Webb-Robertson, 2010) [2] used 35 features and used the SVM approach. STEPP (Webb-Robertson, 2010) [2] achieved an accuracy measure of ~83% with SD of less than 0.038. SD is calculated by first generating ROC curve.

STEPP (Webb-Robertson, 2010) [2] used the following proteotypic peptide features shown on Table 1:

Table 1.1: Proteotypic peptide features STEPP (Webb-Robertson, 2010) [2]

Feature Index in STEPP	Feature
1	Length
2	Molecular weight
3	Number of non-polar hydrophobic residues
4	Number of polar hydrophilic residues
5	Number of uncharged polar hydrophilic residues
6	Number of charged polar hydrophilic residues
7	Number of positively charged polar hydrophilic residues
8	Number of negatively charged polar hydrophilic residues
9	Hydrophobicity—Eisenberg scale
10	Hydrophilicity—Hopp–Woods scale
11	Hydrophobicity—Kyte–Doolittle
12	Hydropathicity—Roseman scale
13	Polarity—Grantham scale
14	Polarity—Zimmerman scale
15	Bulkiness
16 to 35	Amino acid singlet counts

(Receiver Operating Characteristic). The area under curve is a good overall measurement of accuracy (AUC). That is the ability to correctly classify a peptide on average. Hence, perfect classification method will have an AUC of one, while a random classifier will have AUC of ~0.5.

AUC have been calculated for the 3 datasets, *S.oneidensis*, *S.typhimurium* and *Y.pestis*. Moreover, for validation across organisms, each classifier is used on the other datasets. For example, the SVM classifier generated from *S.oneidensis* is used to classify the peptides for the remaining two organisms (Webb-Robertson, 2010) [2]. This result on the AUC values shown on Table 2:

Table 1.2: AUC values for within and across AMT dataset evaluation (Webb-Robertson, 2010) [2]

Training organism	Shewanella oneidensis	Salmonella typhimurium	Yersinia pestis
Shewanella oneidensis	0.791	0.827	0.865
Salmonella typhimurium	0.773	0.841	0.857
Yersinia pestis	0.782	0.834	0.879

As stated earlier, the mean for AUC data on table 3 is 0.828 and SD is 0.038.

Our approach aims to complement the success achieved by this method by introducing a new type of feature, Ordered Amino Acid Usage (AAU) that aim to enhance the accuracy. Preliminary results indicate that Ordered Amino Acid Usage (AAU) is a useful feature for peptides identification.

1.3 Background

One of the first approaches to experimentally identify proteotypic peptides associated with a specific MS technology was using an accurate mass and elution time (AMT) strategy that employed high-resolution MS. This generated a set of peptides that could be detected based on mass and elution time profile (Mallick , 2007) [6].

Using standard database search algorithms such as SEQUEST, a list of peptides are identified. This list of peptides called potential mass tags (PMT) (Yates , 1998) [8]. The next stage is validation using high accuracy MS using both mass and elution time. Once this achieved, future identification is done merely by selection of peptides from the AMT database based on AMT measurement. This method is advantageous, particularly, in complex samples such as plasma, because it offers great sensitivity and increased throughput (May, 2007) [9].

Creating an AMT database for all organisms using experimentation is very challenging. Tremendous work has been expended in cataloging peptides identified by MS/MS (Craig , 2005) [10]. One example of such a database is the European Bioinformatics Institute PRIDE database. Available: <http://genesis.ugent.be/pride>, PeptideAtlas, GPM, SBEAMS and PRIDE (Mallick , 2007) [6].

Those databases are very beneficial for evaluating proteomes as they only need to search a subset of potential peptides candidates (Kuster, 2005) [11]. However, populating these databases for new organisms remains a challenge. To overcome those problems, it proposed to use known properties associated with the high probability that a peptide will be identified. Examples of such properties are numbers of basic and acidic residues and

hydrophobicity of the peptide (refer to Table 1). Using those properties, it is possible to predict proteotypic peptides directly from a primary sequence. Success has been reported using shotgun LC-MS/MS and gel-based MS proteomics (Kuster, 2005) [11] (Mallick, 2007) [3] (Tang, 2006) [1].

Webb-Robertson et al. (2010), report an approach for the prediction of proteotypic peptides for AMT studies based on simple sequence-derived properties using a support vector machine (SVM) classification [2]. As discussed in the introduction, this method has the advantage of simulating AMT databases without having to identify the peptides via MS/MS.

Webb-Robertson et al (2010), use three databases collected for organisms *Shewanella oneidensis*, *Salmonella typhimurium* and *Yersinia pestis*. They used a selection of 35 features (List of features on Table 1) for the prediction of proteotypic peptides for LC-FTICR-MS.

Ermir Qeli et al. (2014), use a rank based algorithm called PeptideRank similar to those used in information retrieval and web searches (Qeli, 2014) [12]. They use 574 different numerical peptide features. Examples of such features are 20 peptides relative frequencies of each amino acid, 10 general peptides properties (length, mass, estimated isoelectric point, etc.) and 5,444 averaged physicochemical properties that were extracted from AAindex1 [14] (AAindex is a database of numerical indices representing various physicochemical and biochemical properties of amino acids and pairs of amino acids) (Qeli, 2014) [12].

1.4 Research Methodology

Preliminary results show that the performance of a classifier based only on the 3-AAU feature comparable to the performance of a classifier using peptides properties. An SVM classifier trained using only the 3-AAU features achieve a sensitivity of 89.72% and a specificity of 81.04%. If we compared this with result achieved by STEPP, STEPP achieved average accuracy measure of ~ 0.83 using 35 features (Webb-Robertson, 2010) [12]. We integrated the AAU feature with a subset of the 35 features used in by Webb-Robertson et al. in STEPP [12]. This resulted in an improved classification rate. We, also, noticed that classification differences between AAU approach and the STEPP result in the misclassification of different peptides subsets. This indicates that the some of the features used in STEPP could complement the AAU feature. In addition, we achieved comparable results by using a subset of features rather than all 35 features together with AAU.

1.5 Verifying Webb-Robertson et al. Results using Matlab machine learning built in functions:

We started first by verification of the result that Webb-Robertson et al achieved using the SVM. Webb-Robertson et al have calculated SVM using the linear SVM:

$$f(z) = \sum_i \alpha_i K(z, s_i) + b,$$

Where $(\vec{\alpha}, b)$ defines the separating hyper plane, z is the normalized data, and s_i is the i -th support vector as defined by the training. We used Matlab built-in SVM functions such as *fitsvm*. We also used one of peptide training data sets published as Webb-Robertson et al. The peptide training data set we used is *Yersinia pestis*.

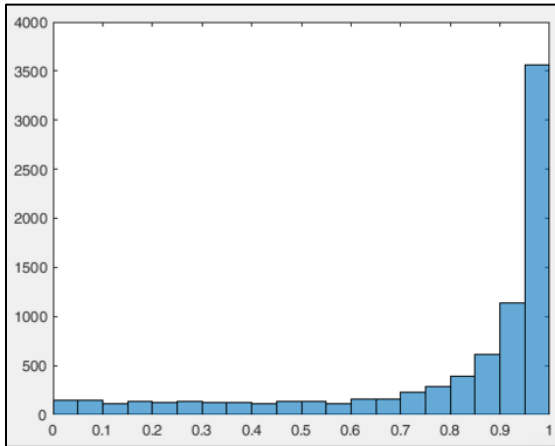


Figure 1.1: histogram for 8,073 identified Peptides probability

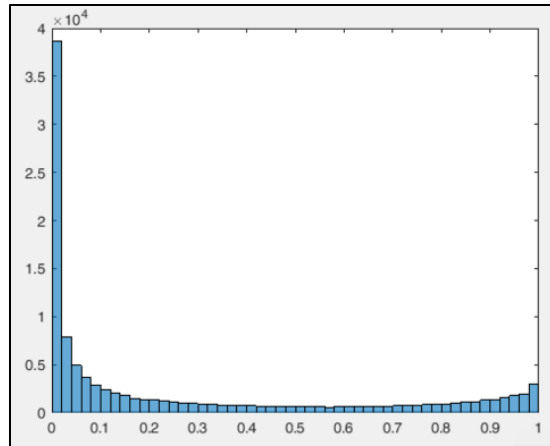


Figure 1.2: Histogram for the 105,399 Peptides probability for unidentified peptides

Diagrams in Figure 2 shows histogram for identified peptide probability, where most of data are close to one. While Figure 3 shows histogram for un-identified peptide with probability data close to zero.

Similarly, Figure 4 below shows histogram for identified peptide score, which shows how far from the separating hyper plane.

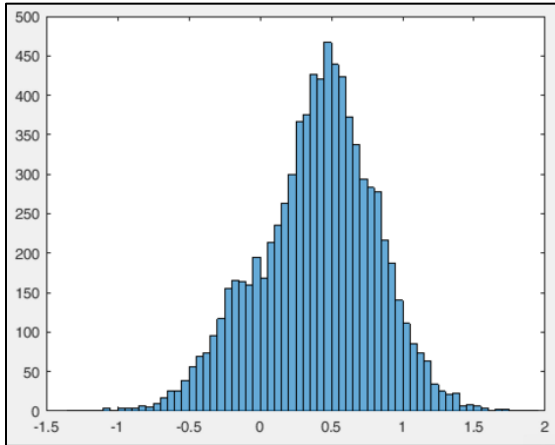


Figure 1.3: histogram for peptides score for identified

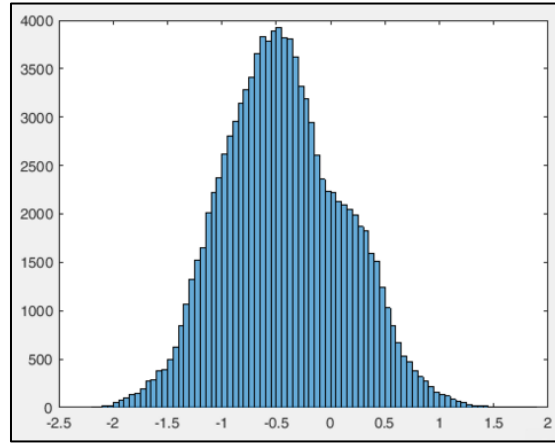


Figure 1.4: peptides score for unidentified.

We evaluated different SVM kernels and noticed that while performance varies between proteotypic and non-proteotypic peptides, the best average result is achieved when the Polynomial kernel is used. For SVM result verification, we used 10-fold cross validation and also calculated the confusion matrix. Accuracy is shown below for different SVM kernels.

Table 1.3: Accuracy for different SVM kernels

Kernel Type	Accuracy
Linear	80.05%
RBF	78.97%
Gaussian	78.97%
Polynomial	81.28%

Below graph gives a visual representation for above table.

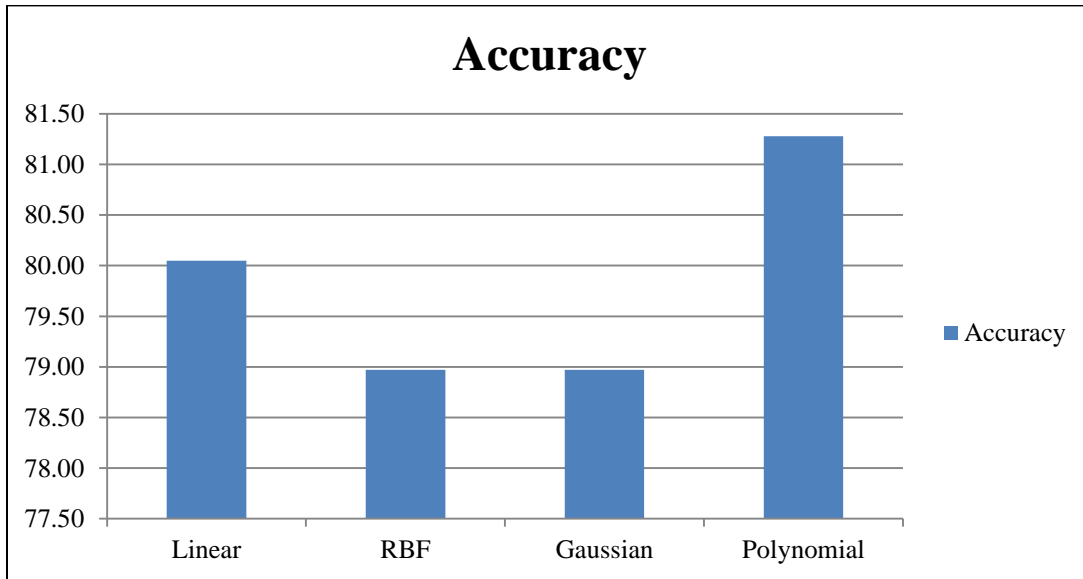


Figure 1.5: Accuracy using different kernel types.

CHAPTER 2

EVALUATION USING AAU

2.1 Evaluating AAU-based Classifiers:

Next, we evaluated ordered adjacent amino acid tuples as a new feature. In order to do that, we performed the following steps:

These steps are used to create separate log-probability matrices for proteotypic peptides and non-proteotypic peptides. These matrices are later used to compute the log-odds of a peptide being proteotypic. Notice, The log odds ratio is a common approach to specifying a decision boundary in sequence classification.

- 1) We calculated the probability that two adjacent amino acids appear in proteotypic and nonproteotypic peptide. This result in two matrices, one for proteotypic peptide and another for nonproteotypic peptide. Each matrix column and row represents a letter that correspond to an amino acid. So for example, columns of matrix are labeled from A... Z and also for rows. Each element of the matrix represents a bond between adjacent amino acids. In the case of these AAU models, overlapping pairs were extracted from the coding sections of genomes. If $\langle a_1 a_2 a_3 \dots a_n \rangle$ is a contiguous sequence of n amino acids, there are $n - 1$ pairs in the sequence, i.e. $\langle a_1 a_2 \rangle$, $\langle a_2 a_3 \rangle$, ..., $\langle a_{n-1} a_n \rangle$. For 2-AAP data, the number of

- 2) occurrences of each of the 400 (202) possible ordered pairs for a genome was tabulated. The histogram is then normalized to sum to 1.
- 3) In order to avoid underflow when multiplying, a natural log is taken for each element.
- 4) Since there are possibly elements with values equal to zero, epsilon is added to all elements to mitigate the issue of taking log of zero.

The following steps were used to calculate log odds of peptide being proteotypic:

- 5) Assuming we have a new peptide “EGALVQK”. We look up the log odds values of the adjacent amino acids “EG”, “GA”, “AL”, “LV”, “VQ”, “QK” in the two log-probability matrices we created above, using for example “E” as a row index and “G” as a column index.
- 6) We sum up the log-probabilities from above step for each 2 adjacent amino acid, so for “EGALVQK”, we sum up probabilities for “EG”, “GA”, “AL”, “LV”, “VQ” and “QK”. Again, we do this twice, once for the proteotypic peptide matrix and also for the non-proteotypic peptide model.
- 7) We derive the log odd ratio by divide the proteotypic log-probability by the non-proteotypic log-probability. If the result is less than one, it’s classified as a proteotypic peptide, otherwise non-proteotypic.

The process described above also repeated for three adjacent amino acids, i.e. proteotypic and non-proteotypic log-probability tables are derived from training data.

The best result was achieved using 3-AAU model. For the 2-AAU model, the sensitivity was 83% and the specificity was 74.59%. In the case of the 3-AAU model, the sensitivity was 89.72% and the specificity was 81.04%. The figure below summarizes this result.

Table 2.1: Accuracy for 2 and 3 adjacent Amino Acids

	Proteotypic	Non-proteotypic
2 Amino Acid bonds (AAU)	83%	75%
3 Amino Acid Bonds (AAU)	90%	81%

Below diagram (Figure 2.1) gives visual representation for same result.

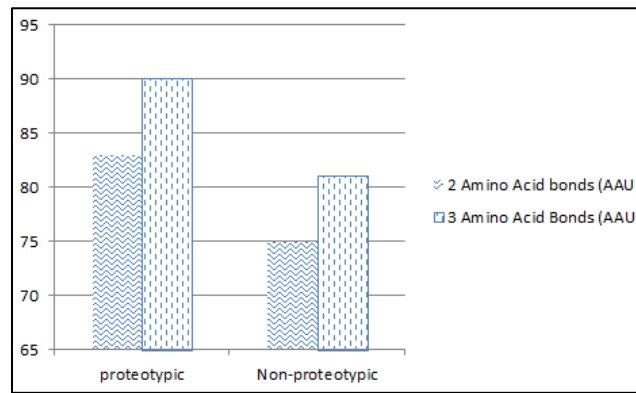
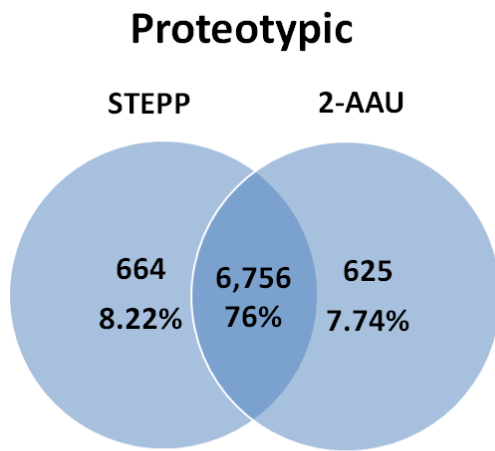


Figure 2.1: Accuracy for 2 and 3 adjacent Amino Acids

This result suggests that the 2-AAU or 3-AAU feature could be combined with a subset of the 35 features used by STEPP to achieve even better accuracy. We demonstrate this in section 5.

As a preliminary step, we created a Venn diagram to depict the classification results of STEPP and our simple 2-AAU-based classifier. In the case of proteotypic peptides, both methods agree on 76% of the true proteotypic peptides, but disagree on roughly an

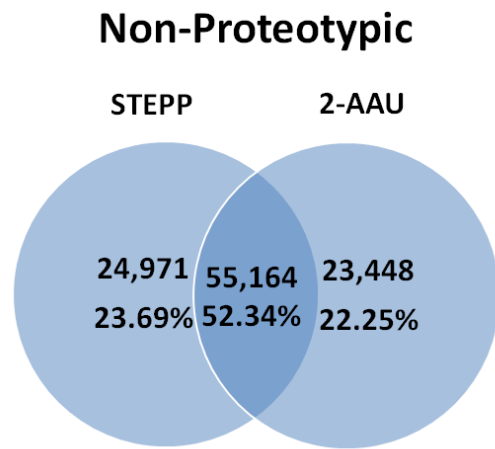
additional 8% of actual proteotypic peptides. This Venn diagram is shown below in Figure 8 for proteotypic peptides and Figure 9 for nonproteotypic peptides. In figure 8, we see that STEPP and the simple 2-AAU-based classifier disagree on a significantly larger ~23% of actual nonproteotypic peptides. Notice, the shaded region in figure 8 is where STEPP and AAU methods agree that this peptide is proteotypic. Likewise, the shaded region in figure 9 is where STEPP and AAU methods agree that this peptide is nonproteotypic.



AAU stand for: Amino Acid Usage.

Notice: Size of Circle doesn't reflect the figure inside it.

Figure 2.2: Venn diagram shows common classification (overlap area) and misclassification errors.



AAU stand for: Amino Acid Usage.

Notice: Size of Circle doesn't reflect the figure inside it.

Figure 2.3: Venn diagram shows common classification (overlap area) and misclassification errors.

2.2 Combining the 2-AAU Features with STEPP Feature:

The next stage is to combine the Ordered Amino Acid Usage (AAU) (2-AA) feature with an appropriate subset of the 35 STEPP features to increase the accuracy of peptide identification. We expected this to be possible since the two methods miss-

classify peptides differently. Hence, there is room for improvement as the feature sets possibly complement each other. The first approach was to simply add the Ordered Amino Acid Usage (AAU) feature to the set of STEPP features by adding one new column that represents the new AAU feature to the matrix that contains the 35 feature used in STEPP (Webb-Robertson et al.). The new column is created by calculating log odds values for each peptide.

Table 5 below shows the improved accuracy after combining the two methods (AAU and STEPP).

Table 2.2: Accuracy for 35 Features and 2-AAU feature combined

Kernel Type	Accuracy (2-AAU)
Linear	82.6%
Gaussian	81.1%
RBF	81.1%
Polynomial	83.5%

Below diagram represent the table above:

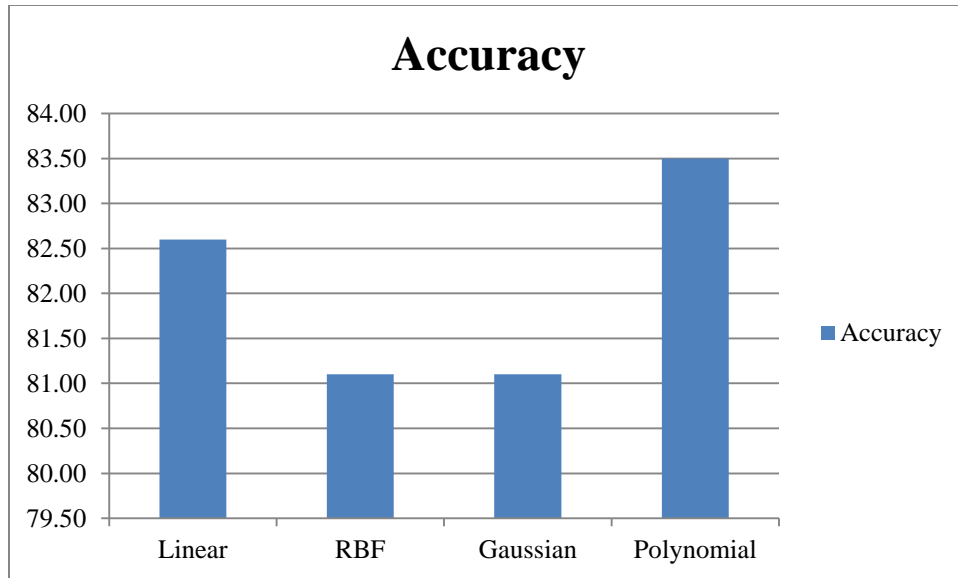


Figure 2.4: Accuracy for 35 Features and 2-AAU feature combined

Comparing the result (Table 5) that with previous result that uses STEPP 35 features only (Table 3), indicate there is some improvement. Below Figure (11) compare the two methods. In the next section we describe a subset of features that achieve similar results as that achieved by using all of these features.

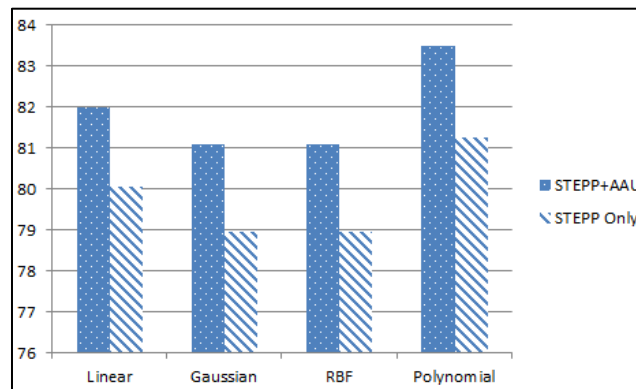


Figure 2.5: Comparing STEPP 35 feature with AAU+STEPP. AAU her is 2-AAU

Likewise, we repeated the test using 3-AAU, (3 adjacent amino acid). 3-AAU gave a much better result:

Table 2.3: Accuracy for 35 Features and 3-AAU feature combined

Kernel Type	Accuracy (3-AAU)
Linear	86.97%
Gaussian	83.07%
Polynomial	86.93%

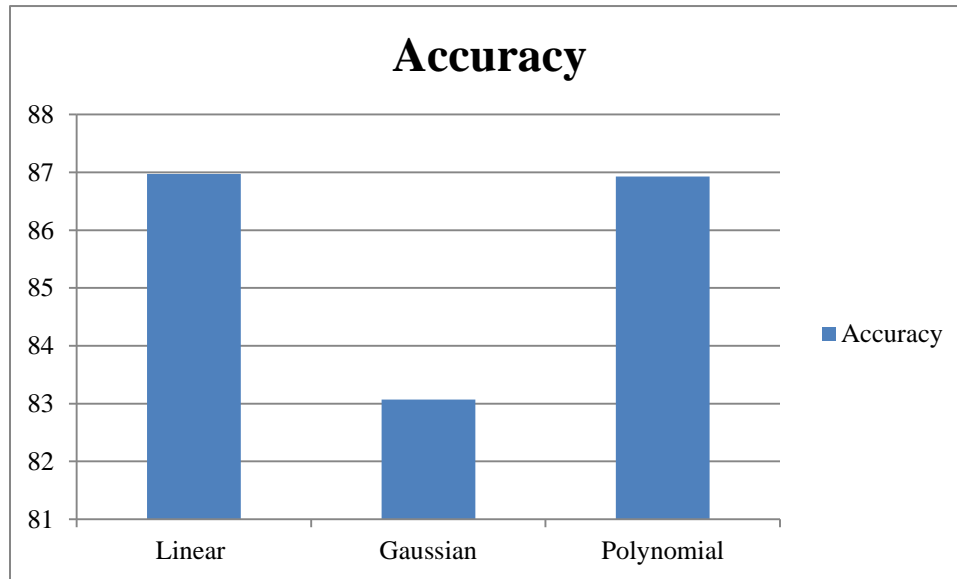


Figure 2.6: Accuracy for 35 Features and 3-AAU feature combined

Notice, unlike 2-AAU, liner kernel gave the best performance. In order to compare the performance for 3-AAU with 2-AAU

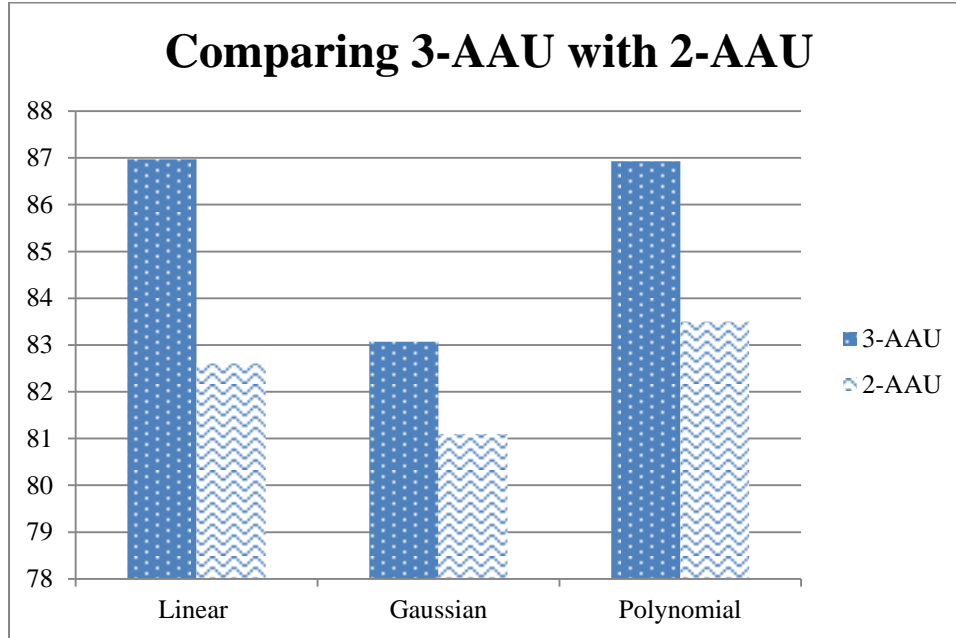


Figure 2.7: Comparing 3-AAU with 2-AAU

Notice by looking at above figure with compare 3-AAU to 2-AAU. There is a major improvement. For example, there is more than 4% improvement in linear kernel.

2.3 Feature Reduction using PCA:

We tried to use Principle Component Analysis (PCA) to give us insight to see which feature of the STEPP 35 feature has more contribution. However, eventually, we have used instead LDA. Nevertheless, for sake of completeness, I'm explaining here the analysis I have done using PCA.

Principle Component Analysis (PCA) for the 35 features has been calculated. The aim is to see if some of the features are dependent on each other and hence eliminate redundant

features. The advantage of feature elimination is that, by reducing the numbers of unnecessary features, the SVM performance may be improved.

When calculating Principle Components, Matlab outputs a variable called “explained” which shows the percentage of how each feature “explains” the variance of the data. The chart of the values of the “explained” vector is shown below:

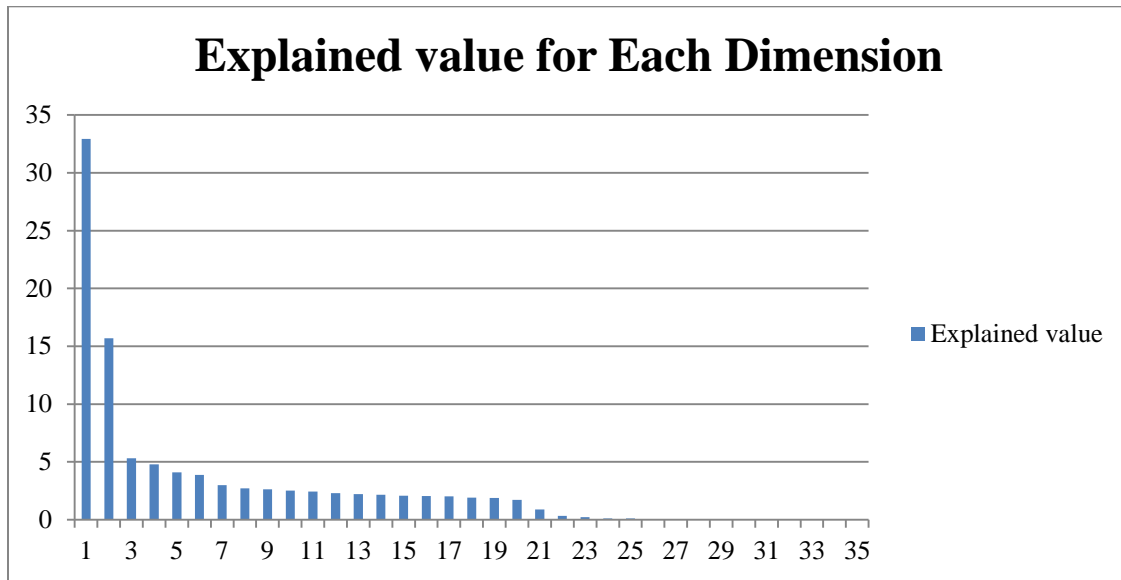


Figure 2.8: Matlab “explained” which shows the percentage of how each feature contributes to the variance of data.

In addition, the empirical and uniform classification error is calculated as a function of the number of included eigenvectors (components). This step is repeated using Linear, Gaussian, and Polynomial kernel types. The graphs for each have been plotted below:

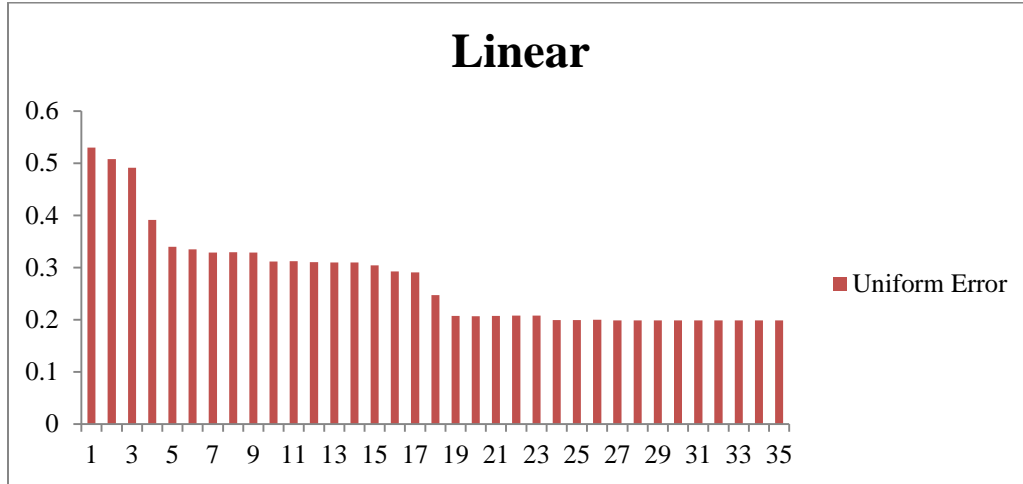


Figure 2.9: Errors calculated as a function of the number of included eigenvectors (components) for Linear kernel

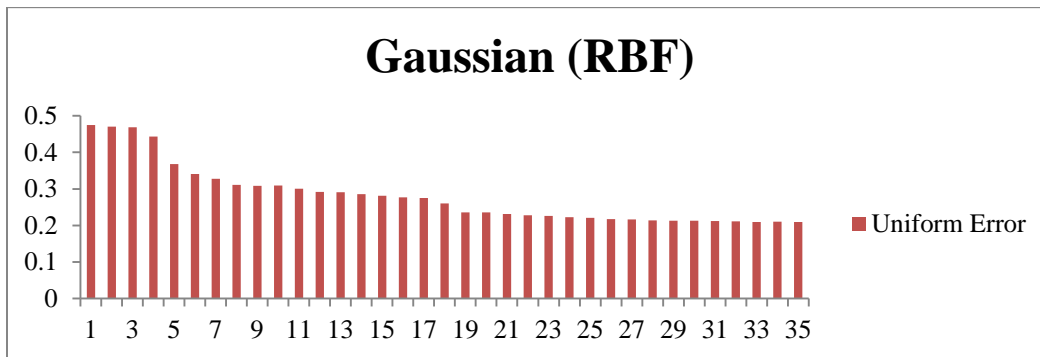


Figure 2.10: Errors calculated as a function of the number of included eigenvectors (components) for Gaussian kernel

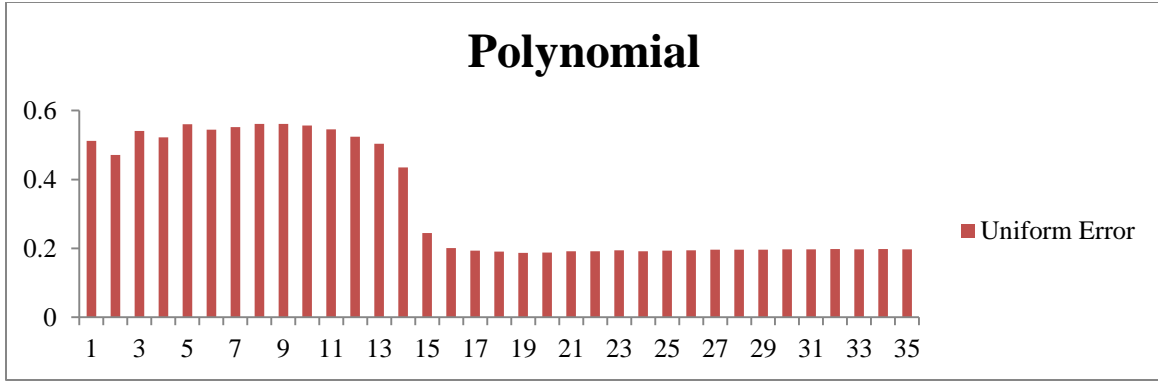


Figure 2.11: Errors calculated as a function of the number of included eigenvectors (components) for Polynomial kernel

CHAPTER 3

RESULT VERIFICATION

3.1 Verification Using Second Data Set:

Our initial work used the *Yersinia pestis* data set that was also used for STEPP (Webb-Robertson) [12]. We identified a second proteotypic peptide data set from a paper titled “CONSeQuence: Prediction of Reference Peptides for Absolute Quantitative Proteomics Using Consensus Machine Learning Approaches” [3]. The data set is for *Saccharomyces cerevisiae*. The data is split on 2/3 for training and 1/3 for verification. The results are shown the figure below.

Table 3.1: Success Rate for Yeast dataset

	Proteotypic	Non-proteotypic
Yeast dataset with 2-AUU	93.22%	81.69%
Yeast dataset without 2-AUU	88.70%	80%

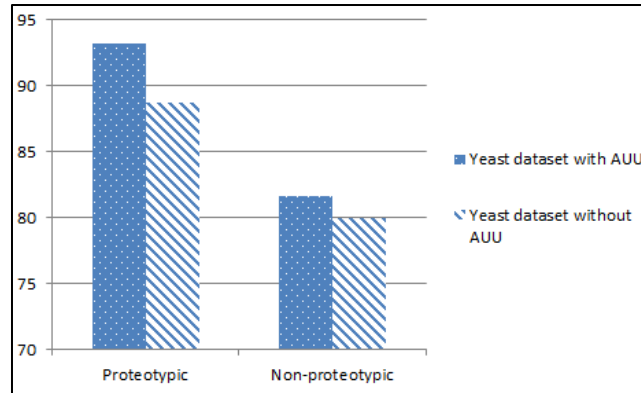


Figure 3.1: Accuracy for Yeast dataset with 2-AAU compared to one without AAU.

3.2 Testing the two data sets combined:

As a verification, we have tested the two dataset combined (*Yersinia pestis* and *Yeast-Saccharomyces cerevisiae*) to see if the result is still consistent. The result has sensitivity of 87.36% and specificity 77.08%. The cross-validated error rate is 17.84%

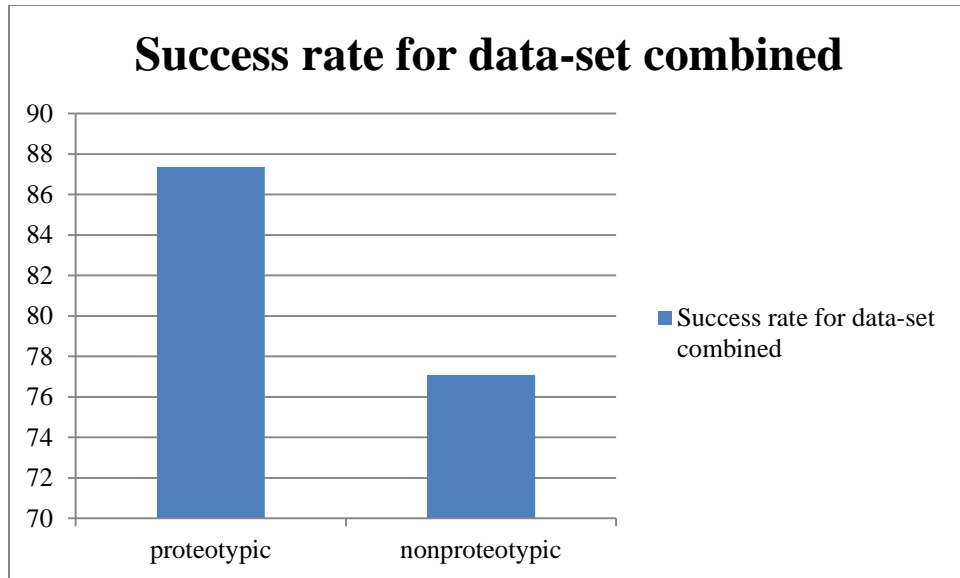


Figure 3.2: Success rate for data-set combined using 2-AAU

CHAPTER 4

FEATURE SELECTION

4.1 Features Selection

One of the objectives of this research is to select a subset of the features used by STEPP to both improve accuracy and reduce computation time. We have used Linear Discriminant Analysis (LDA) to test and see which features contributing more. It is computationally not possible to exhaustively examine all possible combinations of features. Instead we examined each feature individually using LDA by looking at LDA loadings (Figure 19).

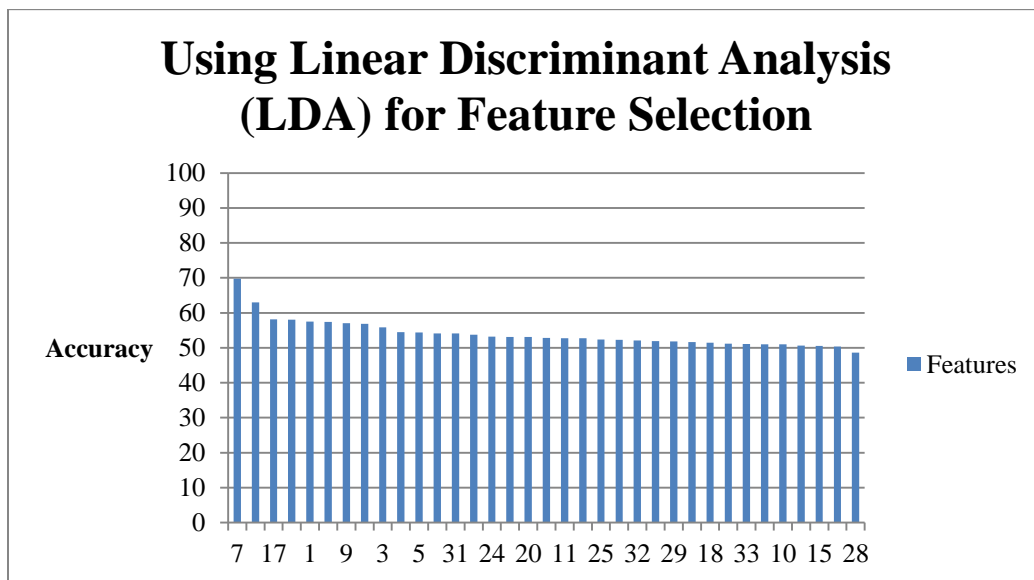


Figure 4.1: Accuracy for each feature of STEPP 35 features alone using LDA. This is used in feature selection to understand which feature has more weight (more important).

We noticed that it's possible to achieve 82% accuracy using 7 features only. These features are:

- Ordered Amino Acid Usage
- Number of positively charged polar hydrophilic residues
- Amino acid singlet counts: Proline (P)
- Length
- Number of non-polar hydrophobic residues
- Number of polar hydrophilic residues
- Number of charged polar hydrophilic residues

Notice that the features in Figure 6 are ordered based on their individual LDA score. We plan on looking at a more sophisticated approach to feature selection to either improve this result or confirm that this is optimal subset of the 35 STEPP features to use in conjunction with ordered amino acid usage.

In order to see how the new selected feature will perform, tests have been repeated with this feature subset only.

Table 4.1: Accuracy of 6 selected feature from STEPP and 2-AAU.

Kernel Type	Accuracy (2-AAU)
Linear	82.59%
Gaussian	81.07%
Polynomial	81.07%

While, below table shows data for 3-AAU with clear improvement:

Table 4.2: Accuracy of 6 selected feature from STEPP and 2-AAU.

Kernel Type	Accuracy (3-AAU)
Linear	86.45%
Gaussian	82.90%
Polynomial	59.47%

Below charts compares the 2 tables above:

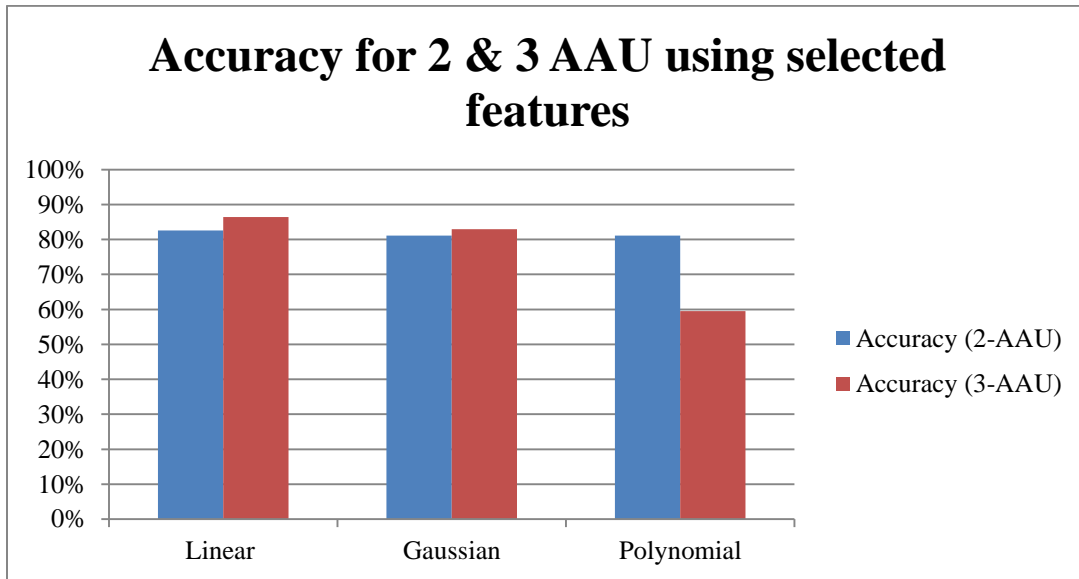


Figure 4.2: Comparing accuracy of 6 selected feature from STEPP with 2-AAU and 3-AAU.

CHAPTER 5

DISCUSSION OF RESULTS

5.1 Accuracy for proteotypic and non- proteotypic peptide separately:

The above accuracy are based on 10-fold cross-validation error (“crossval” in Matlab). However, you might want to see how many proteotypic peptide have been classified correctly and visa-versa. Below table list accuracy for proteotypic and non-proteotypic peptide separately. The table below show the case for STEPP 35 feature with 2-AAU:

Table 5.1: Accuracy for proteotypic and non- proteotypic peptide separately using 2-AAU.

	Kernel Type	Accuracy (2-AAU) proteotypic	Accuracy (2-AAU) non-proteotypic
1	Linear	87.99%	77.190%
2	Gaussian	97.51%	87.257%
3	Polynomial	18.75%	76.81%

Moreover, below table shows the case for STEPP 35 feature with 3-AAU. Notice, there a clear improvement with 3-AAU compared to 2-AAU:

Table 5.2: Accuracy for proteotypic and non- proteotypic peptide separately using 3-AAU.

Kernel Type	Accuracy (3-AAU) proteotypic	Accuracy (3-AAU) non-proteotypic
4 Linear	95.11%	78.89%
5 Gaussian	87.61%	87.68%
6 Polynomial	96.96%	85.53%

The last case is for the 7 selected features:

Table 5.3: Accuracy for proteotypic and non- proteotypic peptide separately using 7 selected feature and 2-AAU.

Kernel Type	Accuracy (2-AAU with selected feature) proteotypic	Accuracy (2-AAU with selected feature) non-proteotypic
7 Linear	89.26%	74.95%
8 Gaussian	95.57%	83.26%
9 Polynomial	18.75%	76.81%

Table 5.4: Accuracy for proteotypic and non- proteotypic peptide separately using 7 selected feature and 3-AAU.

Kernel Type	Accuracy (3-AAU with selected feature) proteotypic	Accuracy (3-AAU with selected feature) non-proteotypic
10 Linear	94.75%	78.185%
11 Gaussian	97.14%	83.90%
12 Polynomial	18.09%	92.19%

The below chart compare the 4 tables above:

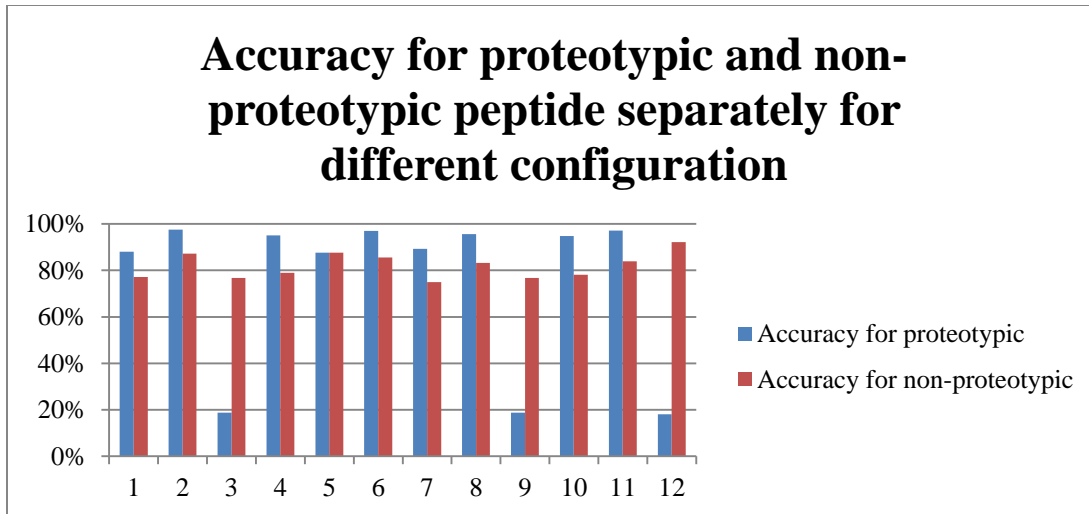


Figure 5.1: Comparing accuracy for proteotypic and non- proteotypic peptide separately using different configuration.

Notice, since this method, unlike the previous one, don't use 10-fold validation, it might be prone to over fitting.

5.2 Prediction Time:

To get an understanding of how long predication time takes for each configuration, we have recorded the required time to predict if a peptide is proteotypic or non- proteotypic (call to predict function). Below table list time of each configuration:

Table 5.5: Prediction Time using different configuration.

configuration	Time in seconds to predict 8,073 peptide
1 Linear (STEPP 35 feature and 2-AUU combined)	6.918
2 Linear (STEPP 35 feature and 3-AUU combined)	3.675
3 Gaussian (STEPP 35 feature and 2-AUU combined)	13..142
4 Gaussian (STEPP 35 feature and 3-AUU combined)	8.250
5 Polynomial (STEPP 35 feature and 2-AUU combined)	12.783
6 Polynomial (STEPP 35 feature and 3-AUU combined)	2.417
7 Linear (STEPP 7 selected feature and 2-AUU combined)	2.521
8 Linear (STEPP 7 selected feature and 3-AUU combined)	1.862
9 Gaussian (STEPP 7 selected feature and 2-AUU combined)	10.287
10 Gaussian (STEPP 7 selected feature and 3-AUU combined)	14.454
11 Polynomial (STEPP 7 selected feature and 2-AUU combined)	2.565
12 Polynomial (STEPP 7 selected feature and 3-AUU combined)	1.967

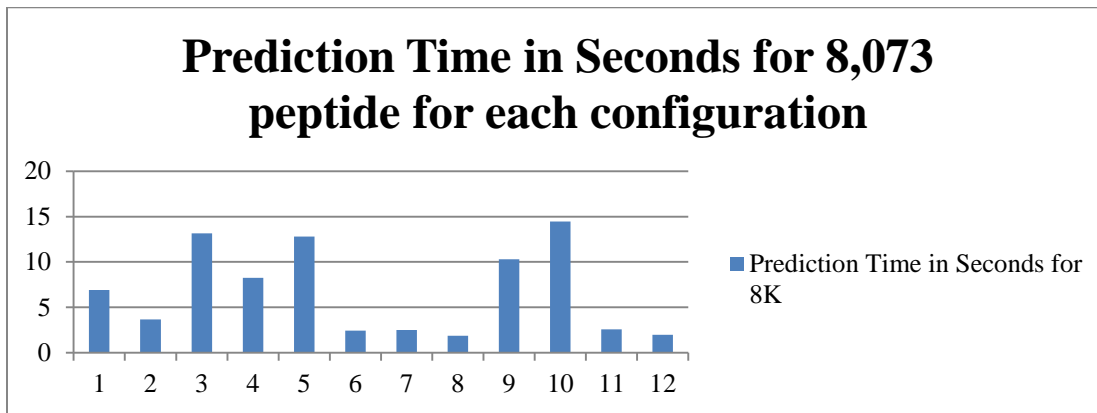


Figure 5.2: Comparing prediction Time using different configuration.

Notice the fastest prediction time happened when linear kernel with selected feature from STEPP and 3-AAU combined.

5.3 Receiver Operating Characteristic (ROC) Curve for different Configuration:

Receiver Operating Characteristic (ROC) curves for different configurations have been generated and area under the curve (AUC) values have been calculated.

Below ROC curve shows ROC with different Configuration.

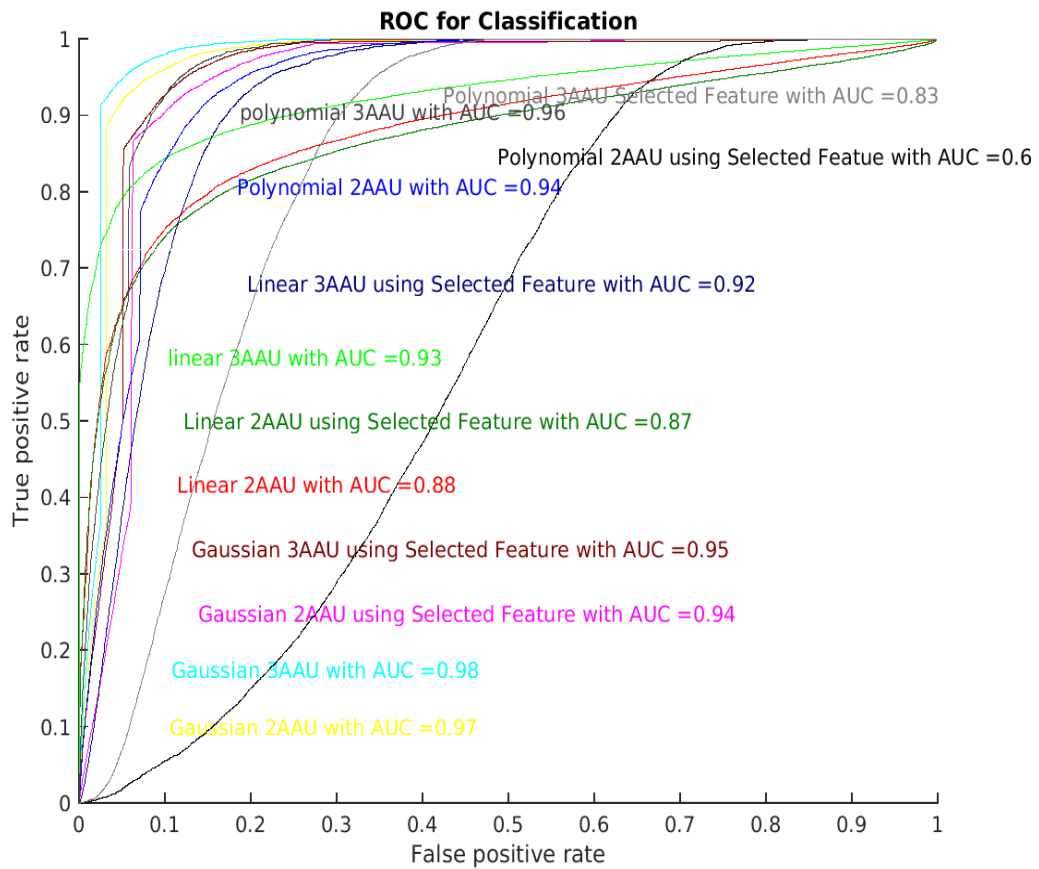


Figure 5.3: ROC with Polynomial kernel, 2-AAU and 35 STEPP features.

Above configuration have been summarized on below table and chart:

Table 5.6: AUC values for different configuration.

Configuration	AUC
1 Gaussian (STEPP 35 feature and 3-AUU combined)	0.98
2 Gaussian (STEPP 35 feature and 2-AUU combined)	0.97
3 Polynomial (STEPP 35 feature and 3-AUU combined)	0.96
4 Gaussian (STEPP 7 selected feature and 3-AUU combined)	0.95
5 Polynomial (STEPP 35 feature and 2-AUU combined)	0.94
6 Gaussian (STEPP 7 selected feature and 2-AUU combined)	0.94
7 Linear (STEPP 35 feature and 3-AUU combined)	0.93
8 Linear (STEPP 7 selected feature and 3-AUU combined)	0.92
9 Linear (STEPP 35 feature and 2-AUU combined)	0.88
10 Linear (STEPP 7 selected feature and 2-AUU combined)	0.87
11 Polynomial (STEPP 7 selected feature and 3-AUU combined)	0.83
12 Polynomial (STEPP 7 selected feature and 2-AUU combined)	0.60

5.4 Limitations and key Assumptions

There are three factors to govern the likelihood of observing a peptide in a proteomics experiment: One, the chemical properties of the peptides and its parent protein. Two, the limitation of the peptides identification protocol, including the pre-processing of the sample, the MS instruments and software tools used for mass spectrum analysis. And three, the abundance of the peptides in the sample that compete with this peptides in the identification procedure (Tang, 2006) [1].

We used the same definition of proteotypic peptide that Webb-Robertson et have used. Proteotypic peptides are those that have been included in the ATM database at any time that the parent protein is observed, rather than requiring minimal observations of peptides (Webb-Robertson, 2010) [2].

The selection of peptides training set is a very crucial step in machine learning. For the binary peptide detectability predication problem, both observed and non-observed peptides should be represented in the training set to avoid bias and over-fitting in the later learning process. Ideally there should be no bias against specific protein classes (Qeli, 2014) [12].

In our analysis we used peptides that have been provided by Webb-Robertson et al. Other peptides samples will be evaluated.

CHAPTER 6

CONCLUSION

6.1 Contributions

The aim of this thesis is to help improve the accuracy of peptides identification and classification which have been gaining momentum due to their ability to generate accurate quantitative data that is mostly relevant to system biology studies and clinical use.

This thesis will explore bonds between amino acids as a new identification feature. As mentioned previously, this new feature will be used to complement the existing 35 features used by Webb-Robertson et al. and reduce the unnecessary features in order to optimize Support Vector Machine (SVM) performance.

6.2 Summery

The most important conclusion of this research is that, the use of AAU feature representing bonds between adjacent amino acids improves proteotypic peptide prediction. The 3-AAU model is superior to the 2-AAU model. In addition, we used LDA to select a subset of six of the STEPP features. Together with the AAU feature, a classifier based on these features achieves classification accuracy similar to that achieved using all of the original features plus AAU.

A paper has been published based on this thesis. Citing of the paper is:

Ahmed Al-qurri and John Rose. "Improving Peptide Identification By Considering Ordered Amino Acid Usage." *Bioinformatics and Computational Biology* (2017): 203-208.

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