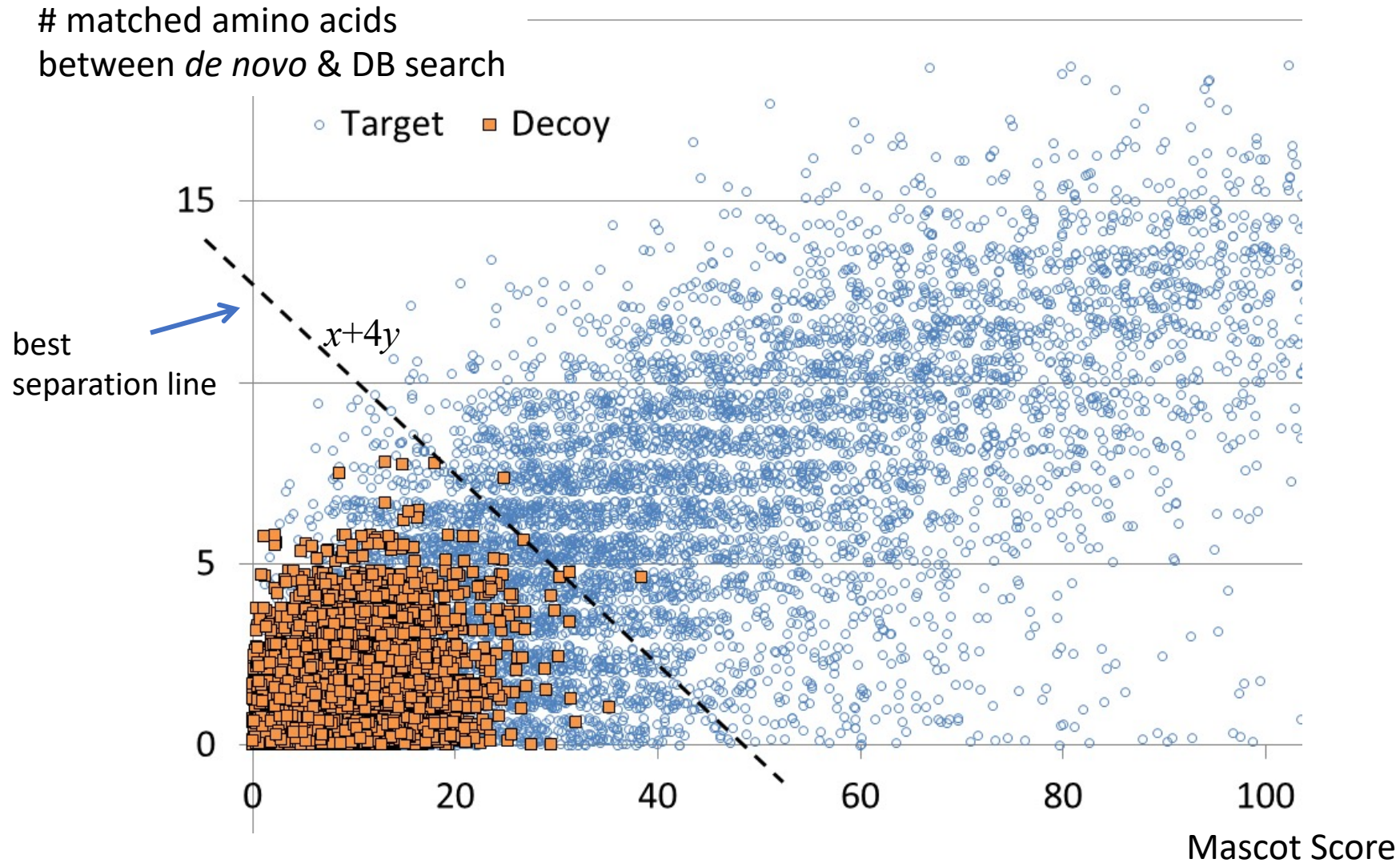


Spectrum Prediction with DNN

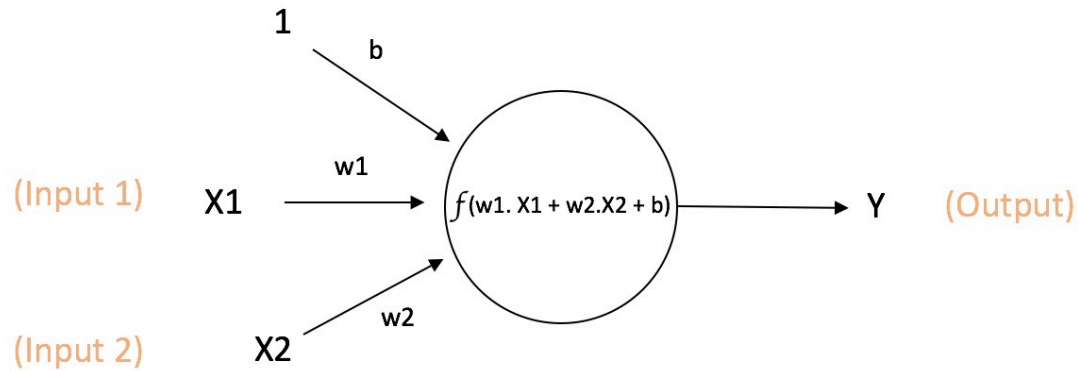
Machine learning

- We've briefly used machine learning twice now:
 - Use a decision tree to score an amino acid in a de novo sequence.
 - Combine multiple score features in database search.

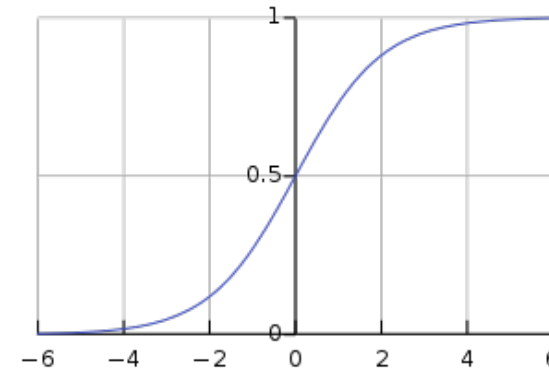
Use multiple features in PSM score



Combine Multiple Features Together



Output of neuron = $Y = f(w1.X1 + w2.X2 + b)$



$$y = \frac{1}{1 + e^{-z}}$$

Activation function

- Train the coefficients w and b to maximize the separation of true and false data points.
- For training, a cost function is defined and there are optimization algorithms to minimize the cost.
- Under certain cost function and sigmoid activation, this is equivalent to the logistic regression.

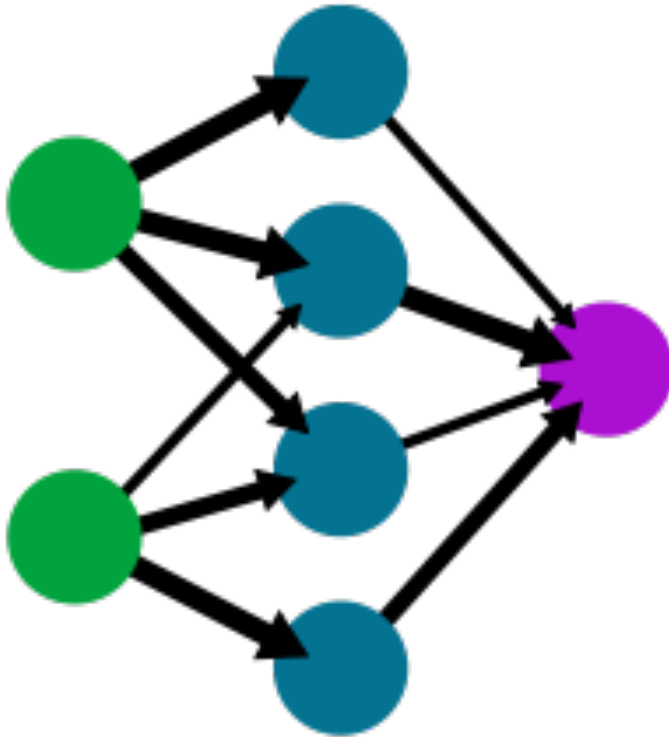
Training

- Known correct (input, output) pairs.
- A cost function.
- Adjust the parameters gradually to reduce the total cost over all training data: gradient descent.
- Training, validation and testing data are separate.
- Training: to learn parameters
- Validation: control the training process to avoid overfitting
- Testing: test the real performance after training

Neural Network

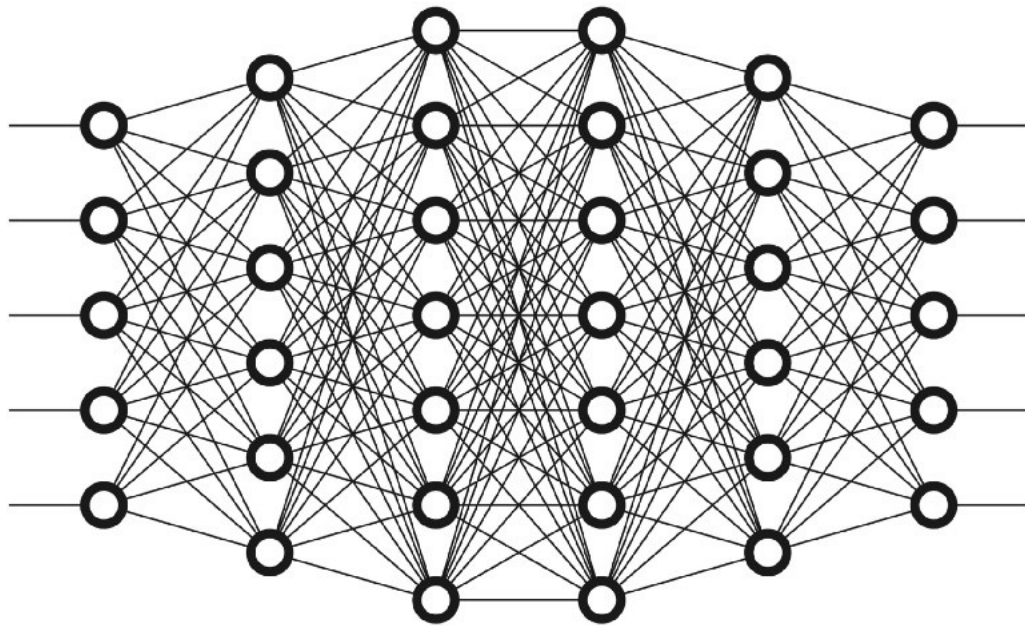
A simple neural network

input layer hidden layer output layer



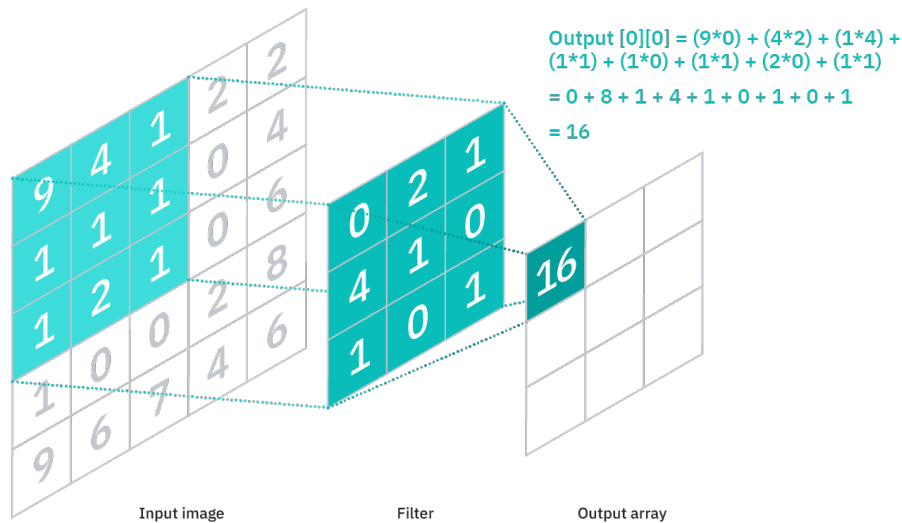
- A neural network just combines many neurons together to fit a more complex nonlinear function.
- Often these neurons are organized in layers.
- The algorithm for training is usually the so-called backpropagation algorithm.
- Main idea behind backpropagation is gradient descent implemented in a nice way.

Deep Neural Network



- DNN is just a neural network with MANY layers.
- MANY coefficients (parameters) to train.
- Require new training algorithms to both learn fast and avoid overfitting.
- GPU, big data, and new learning algorithm contribute to the development.

Convolutional Neural Network



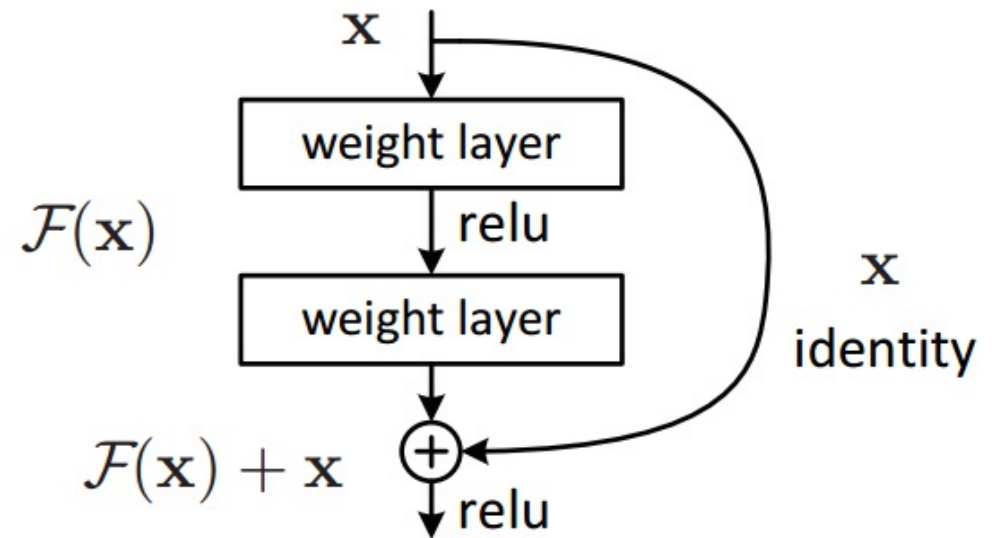
- When the input has spatial similarities, one can reuse the coefficients.
- A “filter” can be seen as a neuron on a local region of the input.
- By sliding the filter over the input array, one can produce the output array. This is called convolution.
- Number of coefficients is reduced significantly.
 - Reduce overfitting.
 - Can afford more layers.
 - Capture the local spatial correlation by focusing on each local region.

Deep Learning

- Similar to CNN, deep learning researchers developed other structures to connect between layers that can boost up the learning performance.
- Some of these common structures can be reused as building blocks in other learning tasks.
 - Just like programming patterns.
- There are deep learning frameworks that allow the users to assemble the building blocks in a flexible way, and provide the learning and prediction support.
 - Tensorflow, Pytorch etc.

ResNet (Residual Neural Network)

- Another commonly used building block is the residual block.
- Intuitively, each additional residual block uses one or more layers to predict the difference between x and the desired output.
- This approach has proven to both improve the learning performance (both learning speed and accuracy).
- Residual blocks are supported by most of the popular deep learning frameworks.



Spectrum Prediction

ANELLNVK

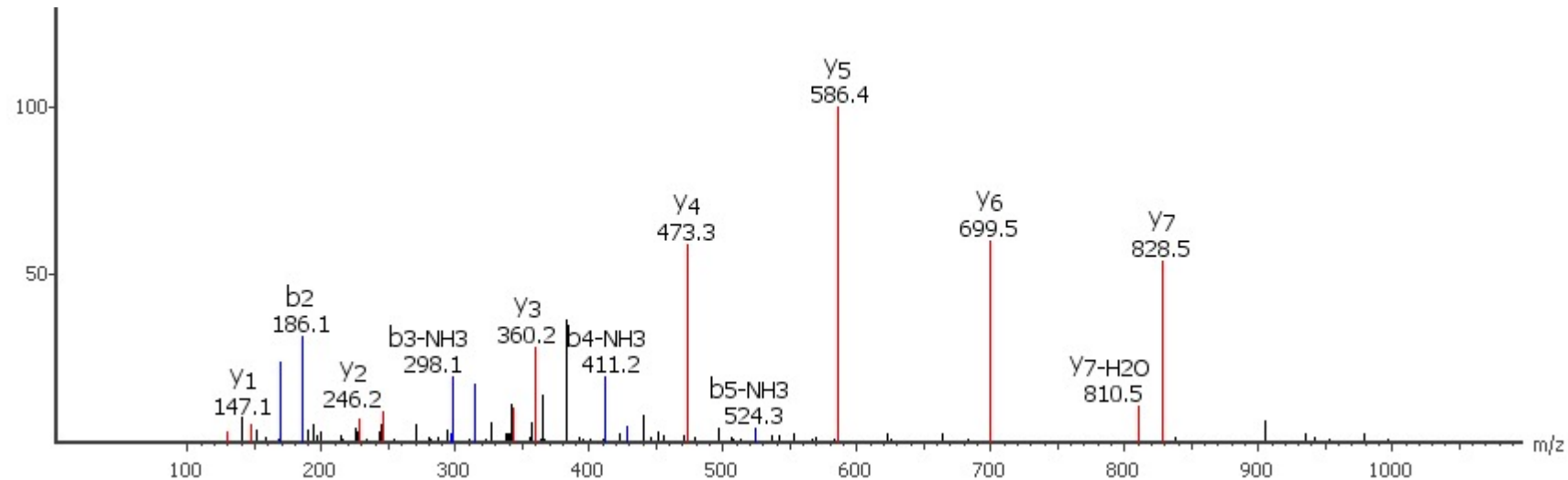
MS/MS



Peptide
Identification



Spectrum
Prediction



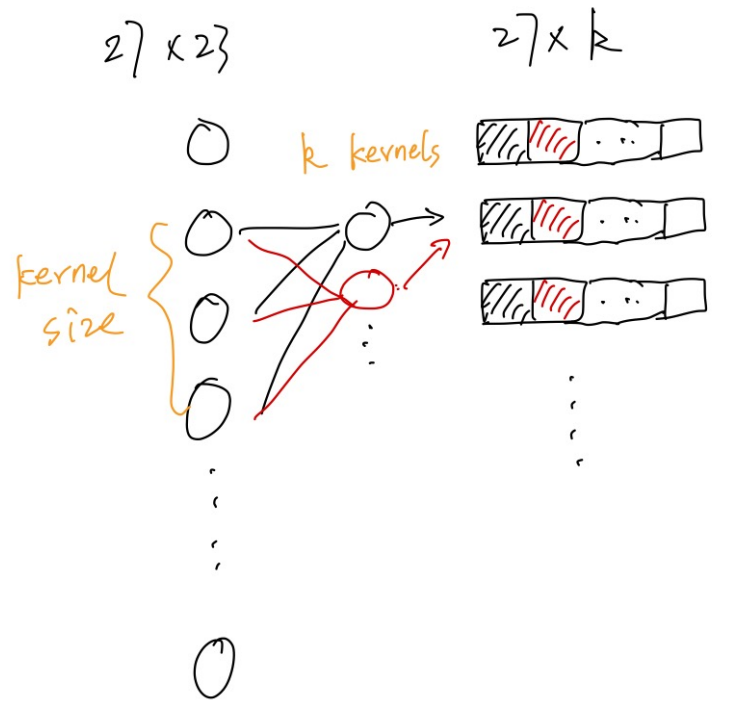
Predict Peptide Detectability

- Let's start with a simpler task to learn the basics: To predict whether a peptide is detectable in a DDA experiment.
- Input: A peptide sequence.
- Output: 0 or 1. (or a probability that the peptide is detected).
- We also have a lot of training data: pairs of (input, true/false).
- Model adopted from the DNN model in following spectrum prediction paper.
 - *Liu et al. Full-Spectrum Prediction of Peptides Tandem Mass Spectra using Deep Neural Network. Anal. Chem. 2020, 92, 6, 4275–4283*
- The paper does not predict detectability but we adopted the model anyway for studying purpose. There can be many different DNN structures for the same task.

Encode a Peptide

- Basic idea: one-hot encoding of amino acids
 - Each amino acid is mapped to a length-20 vector. Only 1 bit is 1, the other 19 bits are 0.
- Peptides have variable lengths.
 - Limit the length to be at most 25AA.
 - If <25AA, then padding with a special character.
- Also encode the two termini (n-term and c-term).
- In total $20+2+1 = 23$ codes are needed. One-hot requires a length-23 vector.
- In total $25+2 = 27$ positions to code. Therefore, each peptide is mapped to a $27*23$ array.
- Note: PTM is not considered.

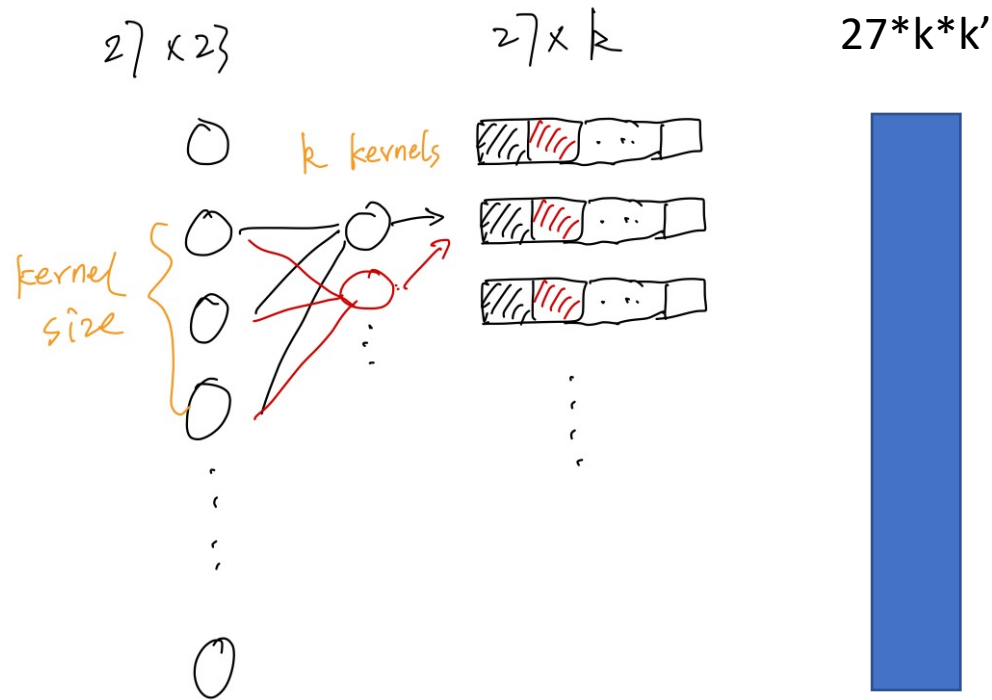
One convolution layer



k : channels, filters, kernels.

- Recall each AA is a 23-dimension 1-hot encoding.
- A kernel is a function that computes a value from s adjacent amino acids. Sliding the same kernel will produce a 27 dimension vector. This is the convolution.
- Padding is needed to keep the dimension 27.
- There are k kernels. So the output of the convolutional layer is $27 \times k$.
- # of parameters is $k \times s$, which is relatively small.
- Activation function for the filters: sigmoid or ReLU (Rectified Linear Unit).

More convolution layers

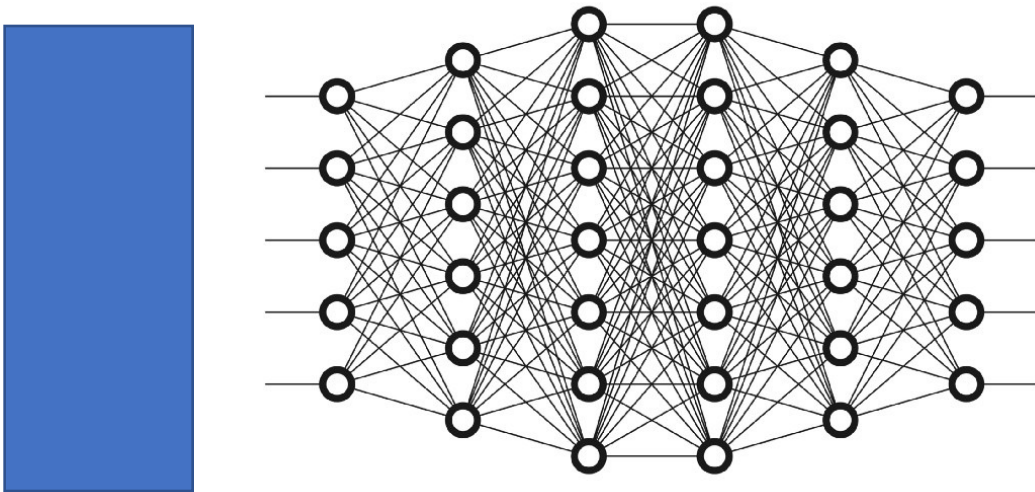


k : channels, filters, kernels.

- For next layer, we can take each channel in the previous layer, and apply k' kernels on it.
- $k \times k'$ kernels, producing $k \times k'$ channels.
- Three practices are often used to avoid exponential expansion of number of parameters
 - $k'=1$
 - Stride > 1
 - Pooling
- With controlling of exponential growth, we can keep adding more and more layers.

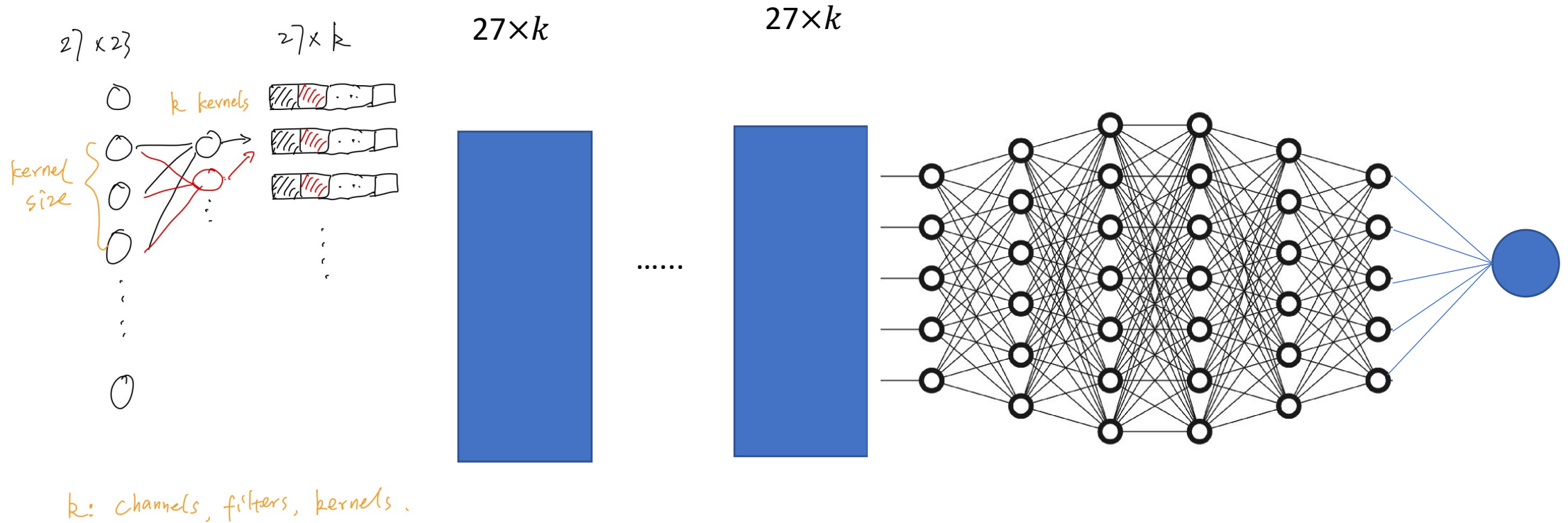
Fully Connected Layers

$n \times k$



- The output of the last convolutional layer is connected to a few fully connected (dense) layers.
- At last, the output layer computes the output.
- Output layer can contain one or more neurons – depending on the actual output format.
- The fully connected layers have the largest number of parameters to learn.

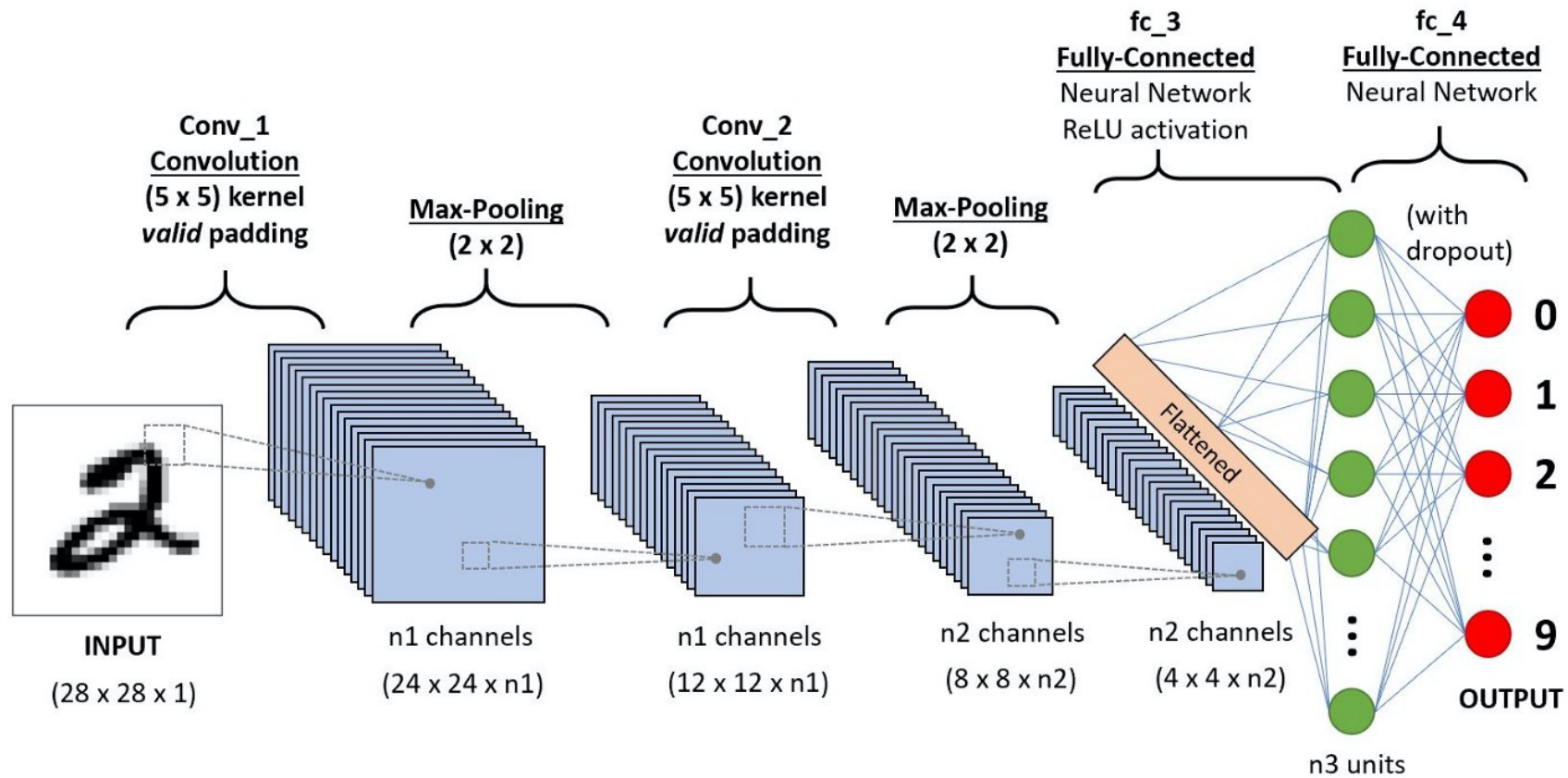
Overview of Whole Network



Learning and Prediction

- Prepare training, validation, and testing data.
- Specify the network structure in a deep learning framework (e.g. Tensorflow)
- Learn parameters with the training data. Control the learning process with the validation data.
- Test the performance on the testing data ONLY after the training is done and parameters are fixed.
- Use the trained parameters to make prediction for future data.

Another Architecture for Handwriting Digit Recognition



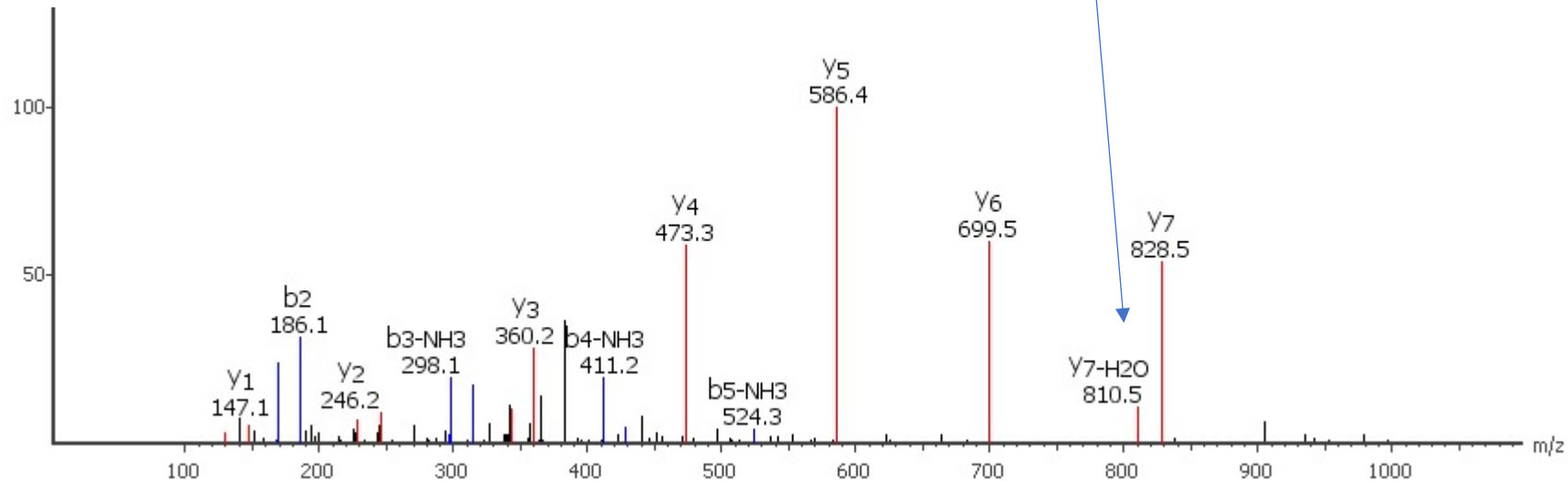
Spectrum Prediction

ANELLLNVK



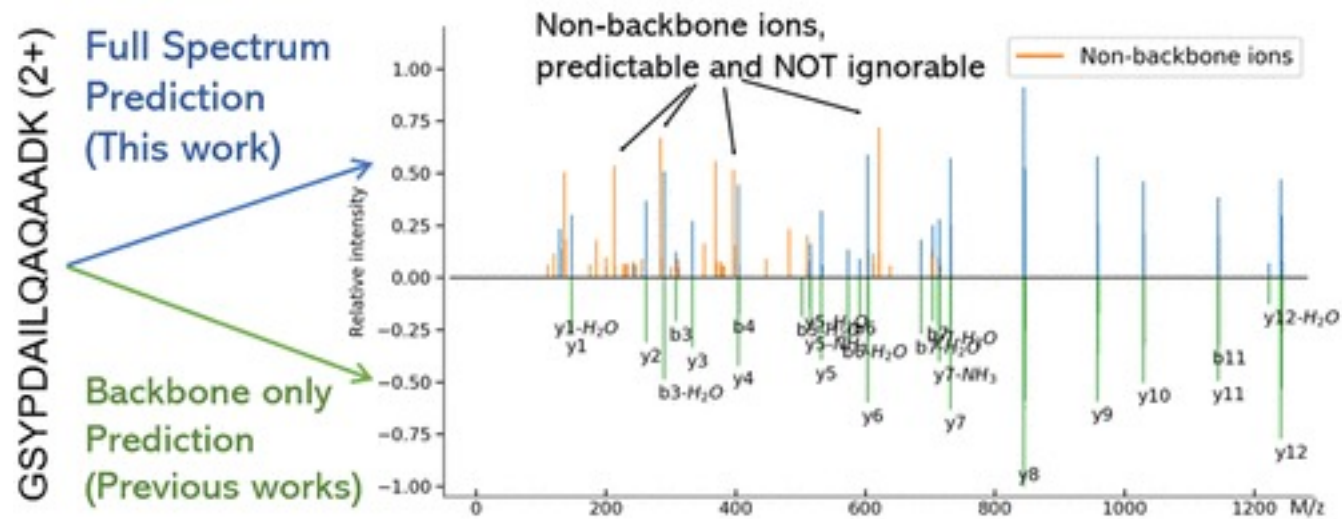
Spectrum
Prediction

Should these minor ions
(not y and b) be predicted?



Spectrum Prediction

- Two lines of research:
 - To predict only the main fragment ions (e.g. b and y ions).
 - To predict the full spectrum.
- Both have been done in literature. We study the full spectrum prediction in the following paper.



Liu et al. Full-Spectrum Prediction of Peptides Tandem Mass Spectra using Deep Neural Network. *Anal. Chem.* 2020, 92, 6, 4275–4283

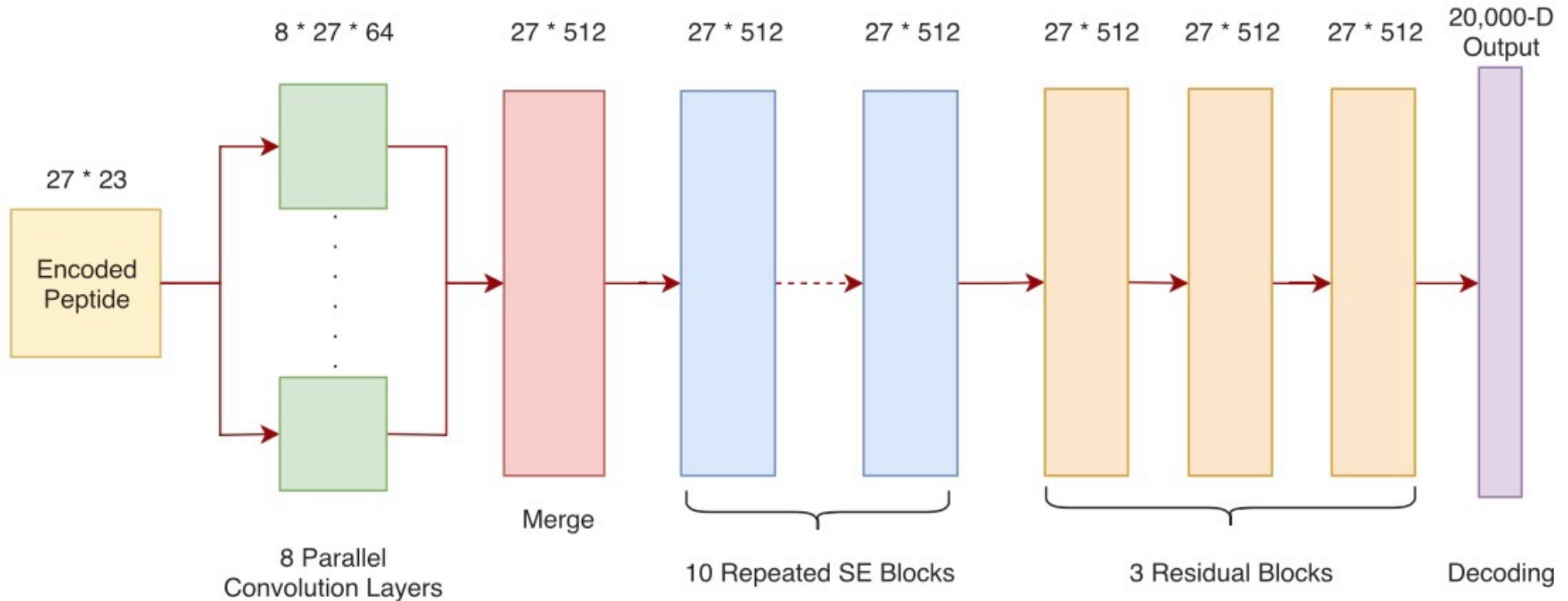
Output Format

- A spectrum usually has a limited m/z range. The work only predicts peaks between 180-2000.
- The spectrum is represented by a sparse one-dimensional (1-D) vector by binning the m/z range between 0 and 2000 with a given bin width. The value stored is the peak intensity.
- With 0.1 Da bin width, a spectrum becomes a 20,000-dimension vector. (Note: most dimensions have value 0).
- The value in each bin is the relative intensity of the tallest peak in the bin.
- Prediction is to predict the values in all the bins.

Input

- Maximum length 25 peptide. Padding if shorter than 25.
- 1-hot encoding of each amino acid, the termini, and padding. Do not distinguish n and c term.
- Additionally provide the amino acid residue mass.
- Thus, 23 dimension vector for each amino acid and termini.

CNN Architecture for Spectrum Prediction

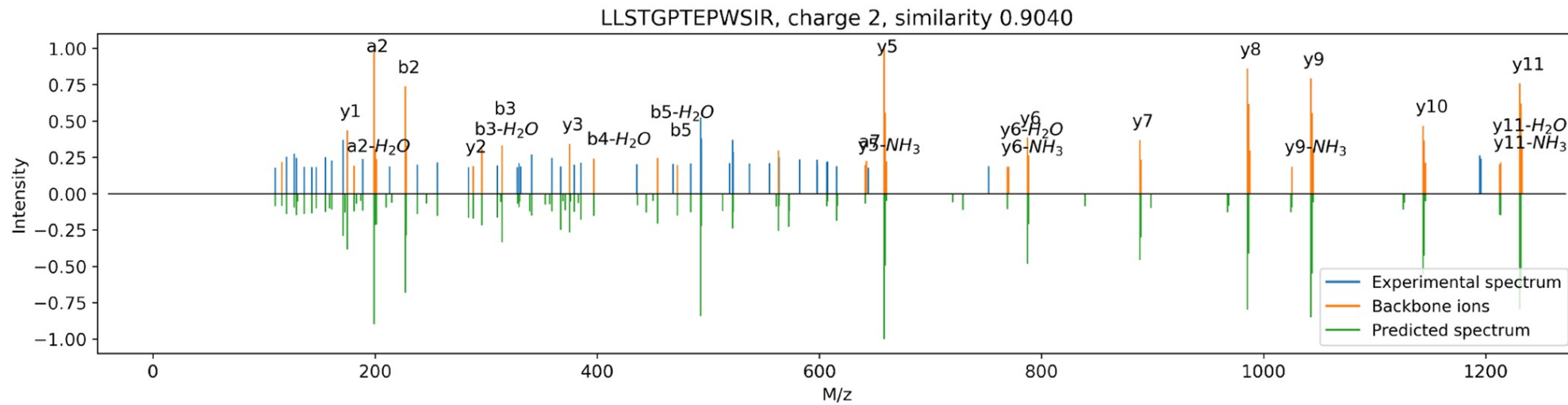


- The 8 parallel convolution layers use kernel size 2 to 9, respectively.
- SE (Squeeze-and-Excitation) blocks are another type of commonly used DNN building blocks.

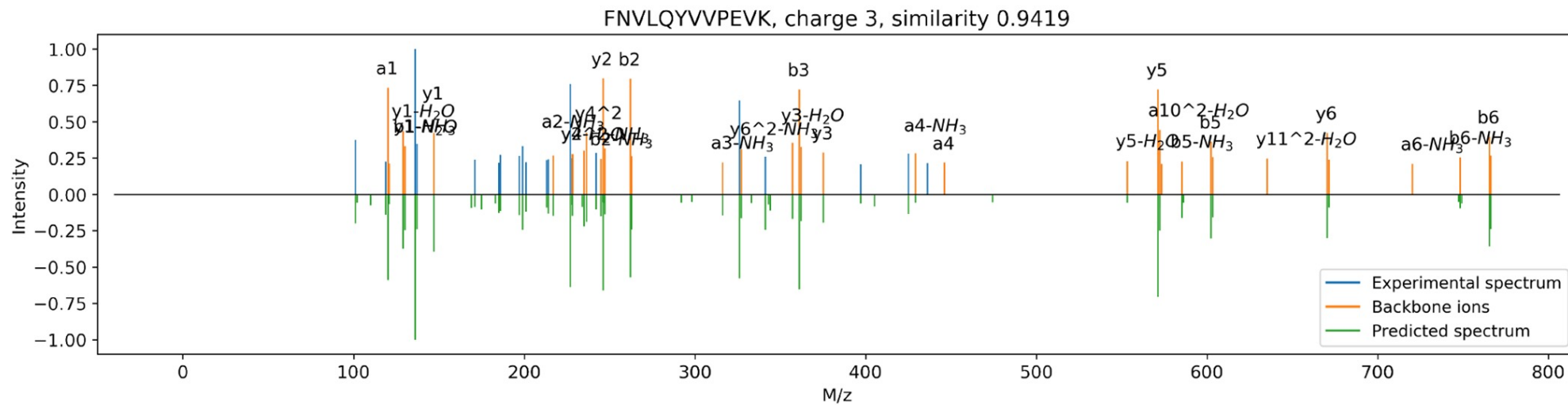
Training

- 2.2M spectra with known sequences were used for training.

Predicted Examples



(a)

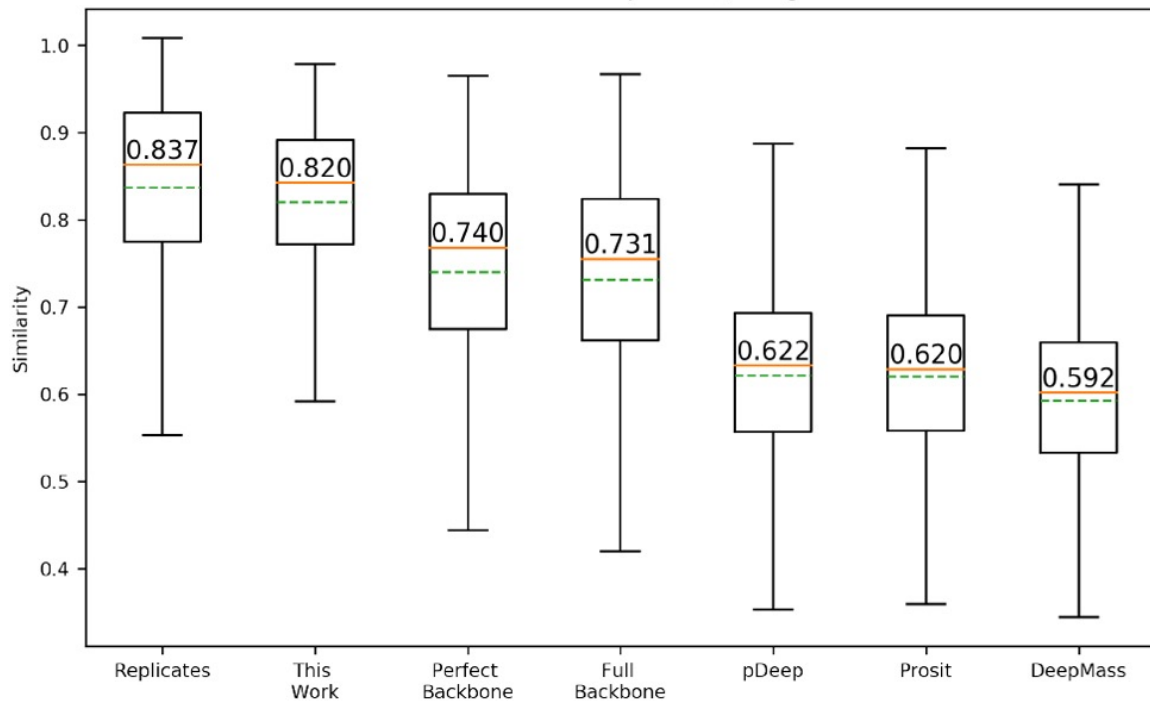


(b)

Comparison to Other Tools

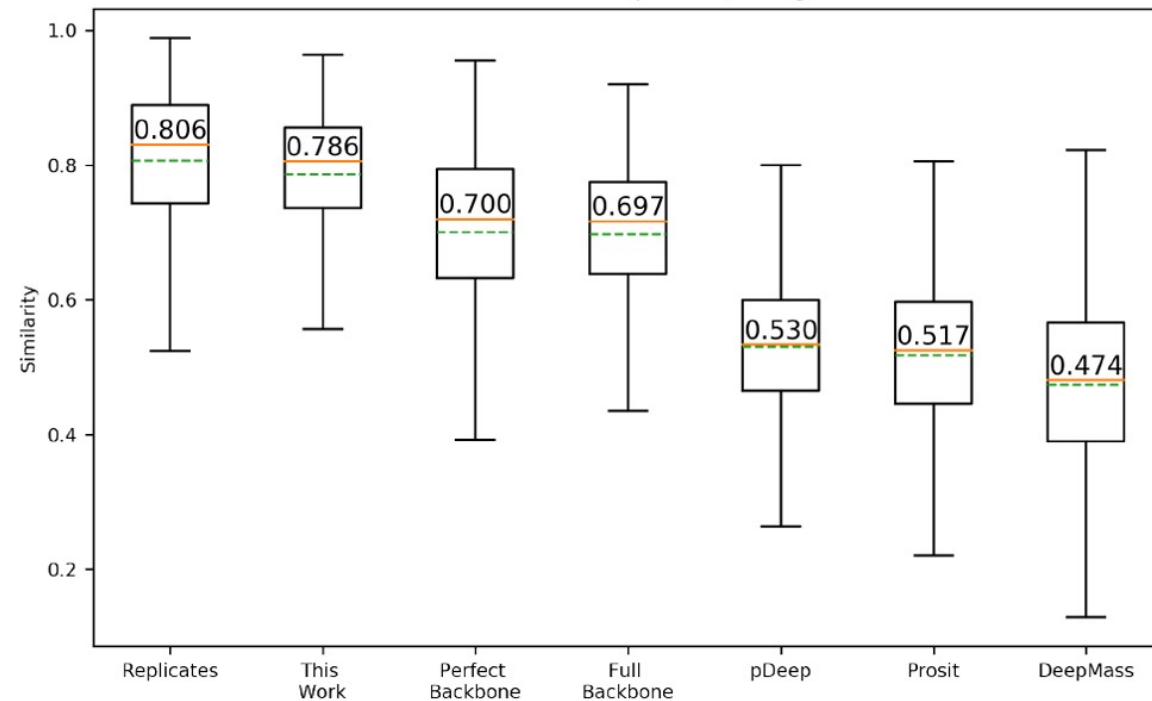
a

Similarities on FULL spectrum, charge 2+

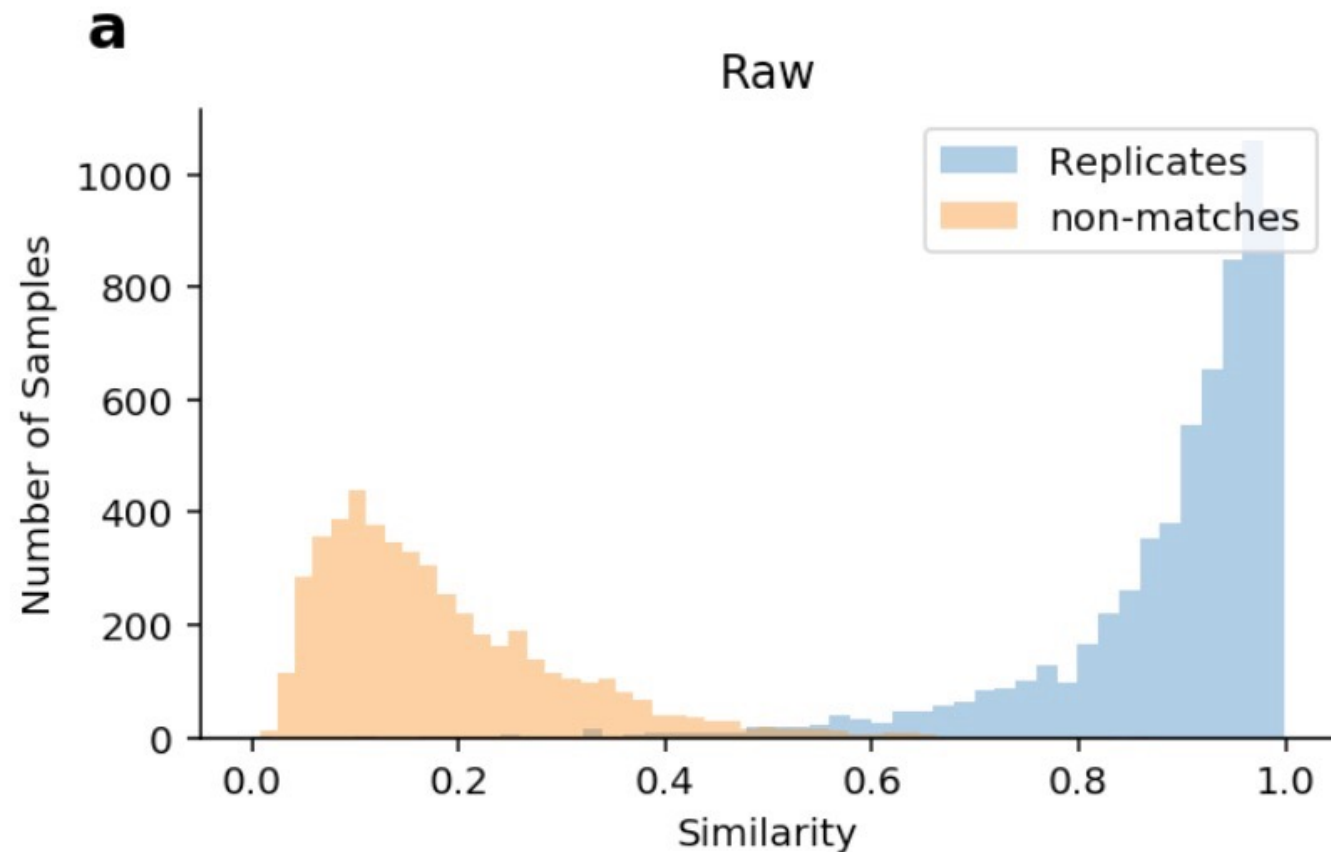


b

Similarities on FULL spectrum, charge 3+



Spectrum Prediction Helps Peptide Identification



If peptide is correct, then its predicted spectrum should match the experimental one with high similarity. Whereas the wrong peptides should have low similarity.