Introduction to deep learning

PREDICTING CTR WITH MACHINE LEARNING IN PYTHON

Kevin Huo
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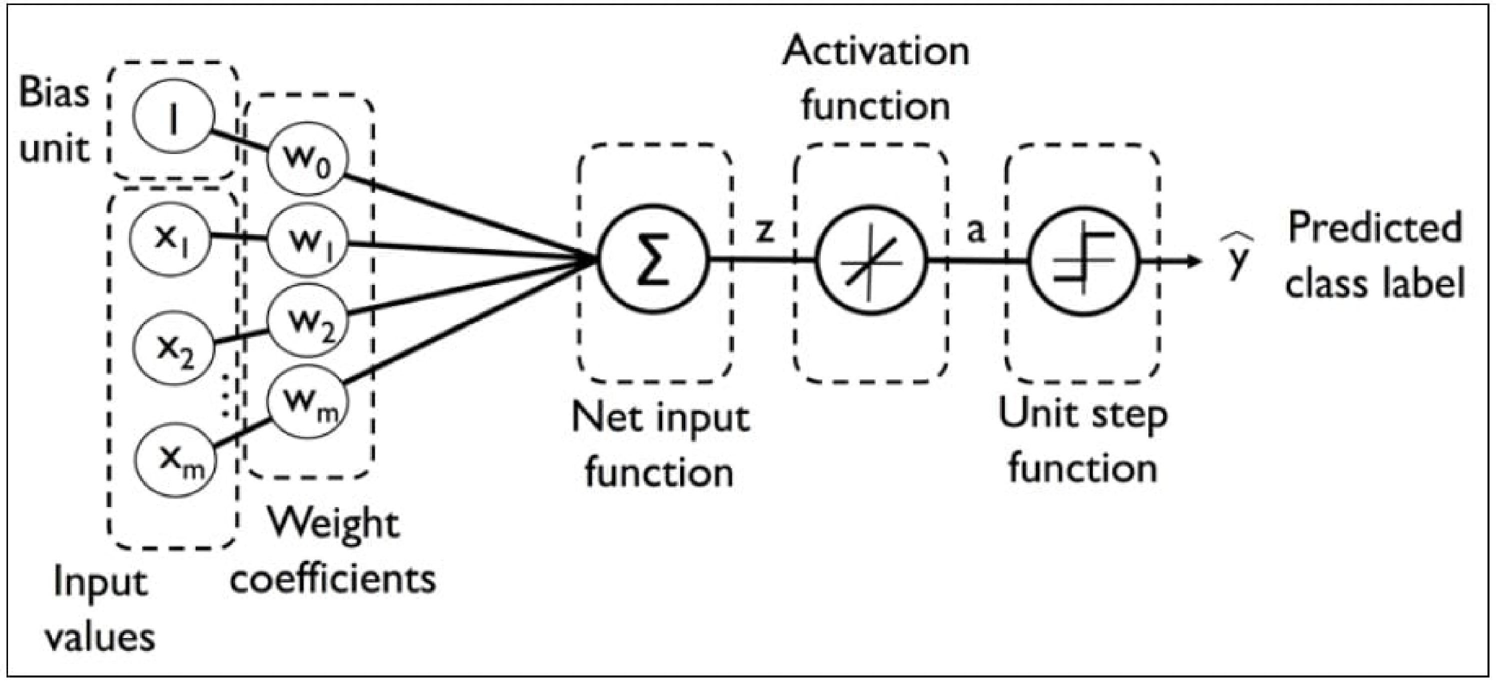
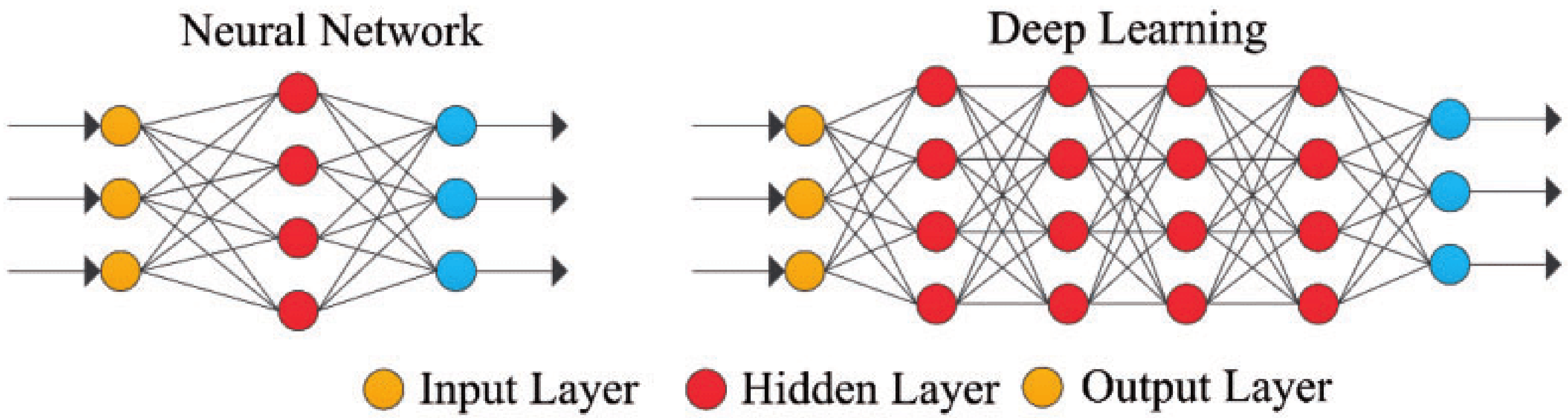
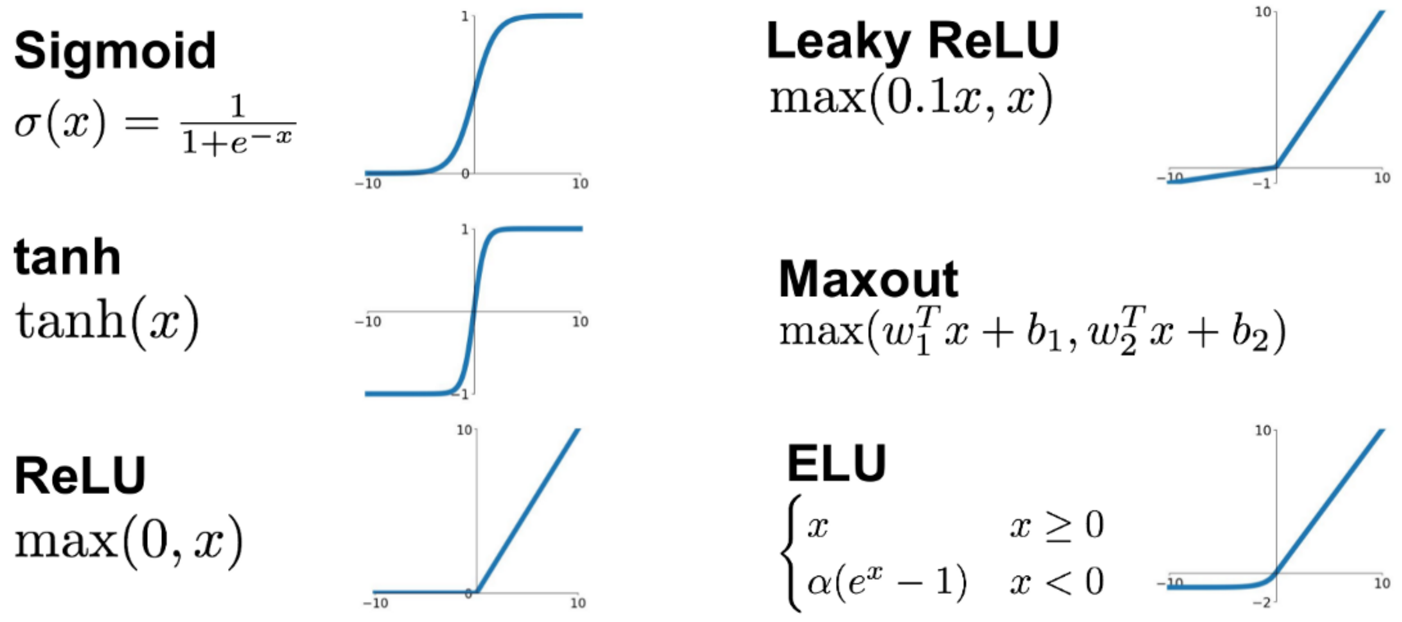
Perceptrons



- Input features are standardized
- Inputs get summed through weights
- Output goes through activation function
- Unit step function to convert output into predicted class

Hidden layers and activation functions





Implementation

```
clf = MLPClassifier()
print(clf)
```

```
MLPClassifier(activation='relu',
              alpha=0.0001,
              ...
              hidden_layer_sizes=(100,),
              learning_rate = 'constant',
              ...
              max_iter=200,
              ...)
```

Other considerations

- Standardization is important before usage
  - `X = StandardScaler().fit_transform(X)`
- Very large networks with many millions of parameters
  - Feature matrices are often "sparse"
- Better performance with more data
  - However, downside is less transparency and longer compute time

Let's practice!

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Hyperparameter tuning in deep learning

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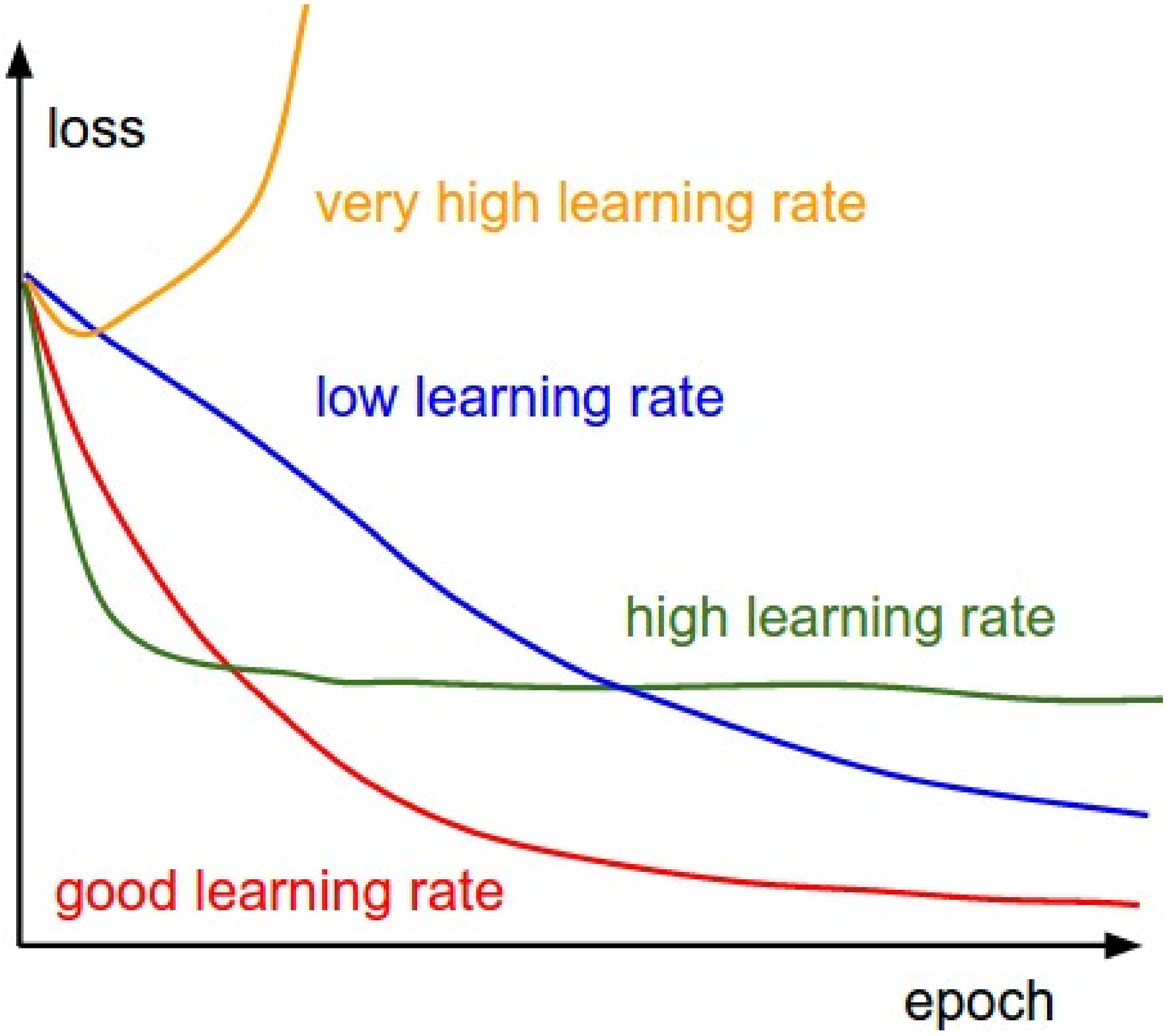
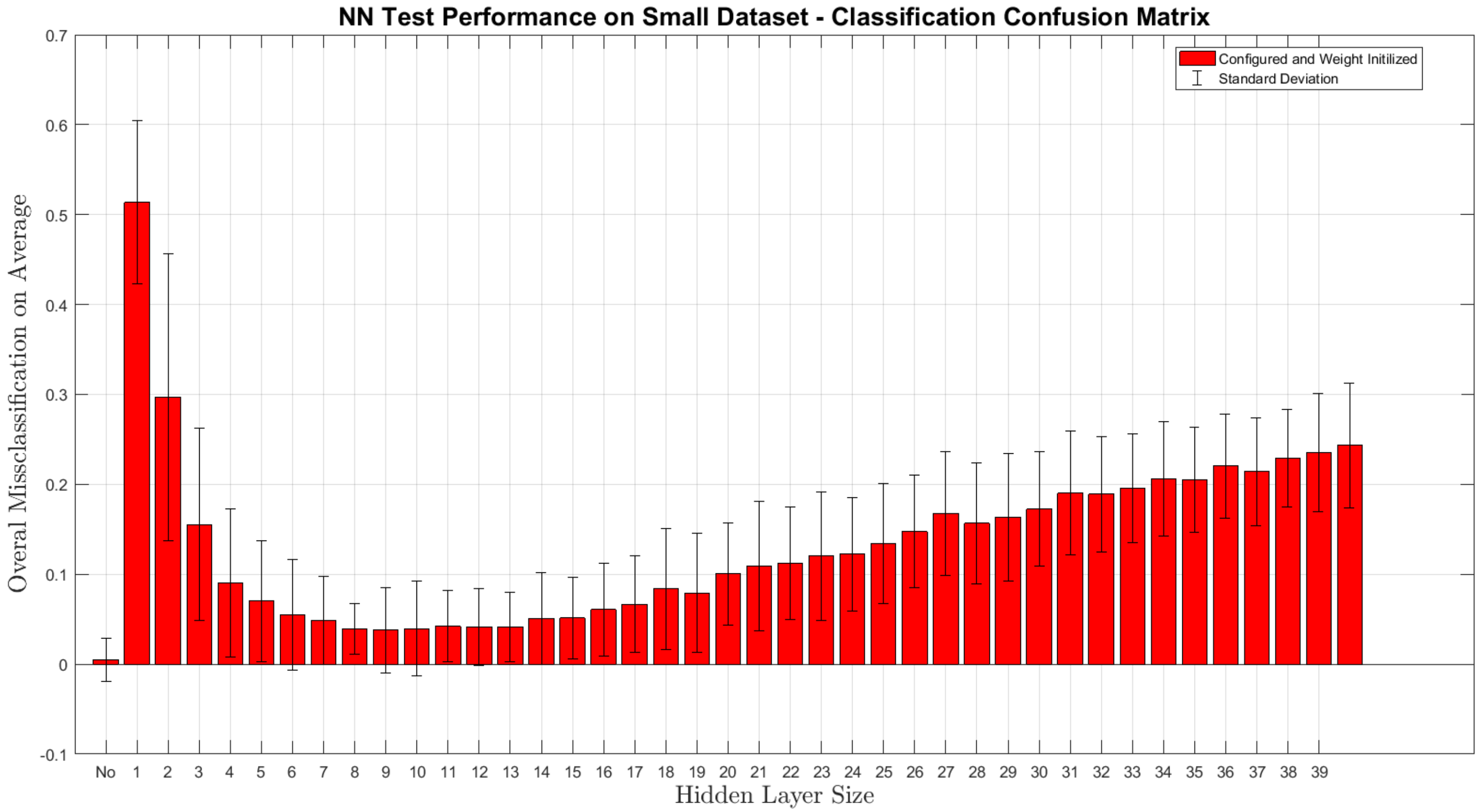
Learning rate and number of iterations



- Weights are updated iteratively
  - Uses back-propagation
- A good learning rate will result in loss dropping quickly and stabilizing
  - Shown in red line
- Too high of a learning rate will result in an "overshoot" and very high loss
  - Shown in yellow line

Choosing hidden layers



- Increase in performance up to certain level of complexity, then drop-off afterwards.

Grid search

```
param_grid = {'max_iter': [10, 20],
              'hidden_layer_sizes': [(8, ), (16, )]}
```

```
clf = GridSearchCV(
  estimator = MLPClassifier(), param_grid = param_grid,
  n_jobs = 4)
print(clf.best_score_)
print(clf.best_estimator_)
```

```
0.65
MLPClassifier(hidden_layer_size = (16,), ...)
```

Real life extensions

- Batch size and epochs are also potential hyperparameters
  - Batch size is for mini-batch (training is done in small batches), and epochs are for the number of iterations through whole training data
- Initialization of weights can vary and affect results
  - Examples of different initializations: uniformly distributed, normally distributed, etc.
- Keras and Tensorflow are often used rather than `sklearn`
  - This is due to limited functionality on `sklearn` in comparison

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Model evaluation

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Precision and recall

- Precision: ROI on ad spend through clicks
  - Low precision means very little tangible ROI on clicks
- Recall: targeting relevant audience
  - Low recall means missed out opportunities on ROI
- It may be sensible to weight the two differently
  - Companies are likely to care more about avoiding low precision compared to low recall

F-beta score

$$F_\beta = (1+\beta^2) \cdot \frac{\text{precision} \cdot \text{recall}}{(\beta^2 \cdot \text{precision}) + \text{recall}}$$

- Beta coefficient: represents relative weighting of two metrics
    - Beta between 0 and 1 means precision is made smaller and hence weighted more, whereas beta > 1 means precision is made larger and hence weighted less
- Implementation available in `sklearn` via: `fbeta_score(y_true, y_pred, beta)`
    - `y_true` is true targets and `y_pred` the predicted targets

AUC of ROC curve versus precision

```
roc_auc = roc_auc_score(y_test, y_score[:, 1])
```

```
fpr = 1 - tn / (tn + fp)
precision = tp / (tp + fp)
```

- Imbalanced dataset: `fpr` can be low when `precision` is also low.
- Let us assume we have 100 TN, and 10 TP and 10 FP.

```
fpr = 1 - 100 / (100 + 10) = 0.091
precision = tp / (tp + fp) = 0.5
```

- Low FPR can lead to high AUC of ROC curve, despite precision being low! Therefore it is important to look at both metrics, along with `F-beta score`

ROI on ad spend

- Same idea from prior: some cost `c` and return `r`

```
total_return = tp * r
```

```
total_spent = (tp + fp) * cost
```

```
roi = total_return / total_spent
    = (tp) / (tp + fp) * (r / cost)
    = precision * (r / cost)
```

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Model review and comparison

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Model review

```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neural_network import MLPClassifier
```

- Logistic regression: linear classifier identifying decision boundary
- Decision trees: tree-format of conditions
- Random Forests: ensemble of Decision Trees
- Neural Networks (MLPs): layers using linear combinations of features with a nonlinear activation function

Model implementation

Similarities

- Feature transformation and regularization
- Fitting via `classifier.fit(X_train, y_train)`
- Predictions via `predict_proba()` and `predict()`

Differences

- Decision Trees: `max_depth` , `min_samples_split`
- Random Forests: `n_estimators` , `oob_score`
- Logistic Regression: `fit_intercept` , `class_weight`
- Neural Networks: `hidden_layer_sizes` , `max_iter`

Model evaluation

- Key evaluation metrics:
  - Confusion matrix: `confusion_matrix(y_test, y_pred)`
  - Precision: `precision_score(y_test, y_pred)`
  - Recall: `precision_score(y_test, y_pred)`
  - F-beta score: `fbeta_score(y_test, y_pred, beta = 0.5)`
  - AUC of ROC curve: `roc_auc_score(y_test, y_score[:, 1])`

Main pros and cons of using neural networks

Pros

- Scalability with data
- Less need to do feature engineering
- More transferable across domains

Cons

- Less powerful on smaller datasets
- Difficult to interpret
- Computationally and financially cheaper

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Wrap-up video

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Chapter 1

- Introduction to CTRs
  - Learned about basic problem from a classification lens
- Overview of machine learning models
  - Practiced with logistic regression on various datasets
- Brief overview of CTR prediction
  - Applied decision trees for CTR prediction

Chapter 2

- Basic exploratory data analysis
  - Looked at specific features and variability with CTR
- Feature engineering
  - Learned hashing and created features from existing ones
- Standardization
  - Applied standard scaling and log normalization

Chapter 3

- Applications of metric evaluation
  - Learned the business interpretations of evaluation metrics through confusion matrices and an ROI framework
- Model evaluation
  - Evaluated precision and recall relative to a baseline classifier
- Tuning models
  - Learned concepts of regularization and cross-validation
- Ensembles and hyperparameter tuning
  - Tuned hyperparameters using grid search for a Random Forest

Chapter 4

- Basic concepts and model
  - Learned the inner workings of neural networks
- Hyperparameter tuning
  - Tuned hyperparameters of neural networks via hidden layers and max iterations
- Model evaluation
  - Computed `F-beta` scores and implications of precision versus AUC of ROC curve
- Model review and comparison
  - Reviewed all models covered and compared them on all evaluation metrics

Thank you!

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