Kepler Exoplanet Detection

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DS207 Final Project

Github: https://github.com/hahnkenneth/mids_w207_fall2024_brendel_hahn_hudda_paterno

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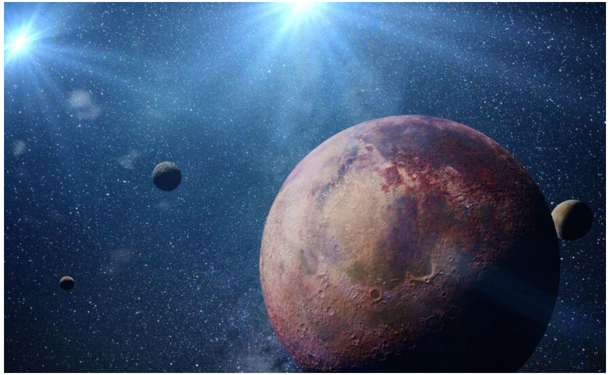
Agenda

1. Background/Motivation
2. Data source/structure
3. Data pre-processing and feature engineering
4. Baseline model: logistic regression
5. EDA
6. Final selected model
7. Evaluation
8. Altering threshold effect on metrics
9. Conclusion

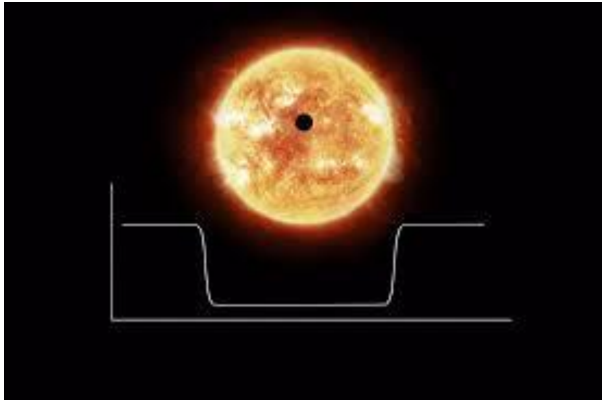
Background

- Exoplanet detection is a cornerstone of modern astronomy
- Provides crucial insights to planetary formation, the potential for extraterrestrial life, and dynamics of distant star systems



- The Kepler Space Telescope operated from 2009 to 2018, which surveyed over 200,000 stars in the Milky Way Galaxy to identify transiting exoplanets - detected by measuring the amount of light it blocks from the star it is orbiting
- Key attributes of confirming an exoplanet detection include the orbital period of the exoplanet, temperature of the star, etc.
- These features form the foundation for a binary classification task: predicting whether an observation corresponds to an exoplanet (1) or not an exoplanet (0).

Motivation



- Scale of data: Kepler telescope dataset contains thousands of observations with numerous features
- Manual analysis is time-consuming, prone to error, and incapable of scaling to datasets from upcoming missions
- Detection accuracy: traditional classification methods may miss subtle patterns in data - advanced feature engineering and optimization can identify non-linear relationships and improve classification accuracy
- Automating the detection process accelerates the pace of discovery, allowing astronomers to focus on further validation and characterization.
- **Goal: We aim to create a ML pipeline that can automate exoplanet detection through binary classification to expedite the process of evaluating exoplanet candidates**

Data Source/Structure

- Kepler Exoplanet Search Results, originates from Kepler Space Telescope observations released by NASA, and accessible on Kaggle
- Dataset includes both confirmed exoplanet and false positives
- 9,576 rows and 49 columns
  - Target variable:
    - Koi_pdisposition: exoplanet (1) or false positive (0)
  - Planetary attributes:
    - Koi_period: orbital period in days of exoplanet candidate
    - Koi_duration: duration (hours) of transit
    - Koi_depth: depth of transit, indicative of planet's size relative to the star
  - Metadata:
    - Kepid: Kepler ID of observed star
    - Koi_score: disposition score indicating confidence level for classification

Data Pre-Processing Pipeline

- Feature Organization
  - Transit Properties, Threshold-Crossing Event Information, Stellar Parameters, KIC Parameters
  - Binary Target encoding: Candidate (1) / False Positive (0)

- Train/Val/Test Split (60/20/20)
  - Used random_state = 207 for reproducibility

Final Output: Clean datasets with no missing values. Binary target. Ready for modeling!

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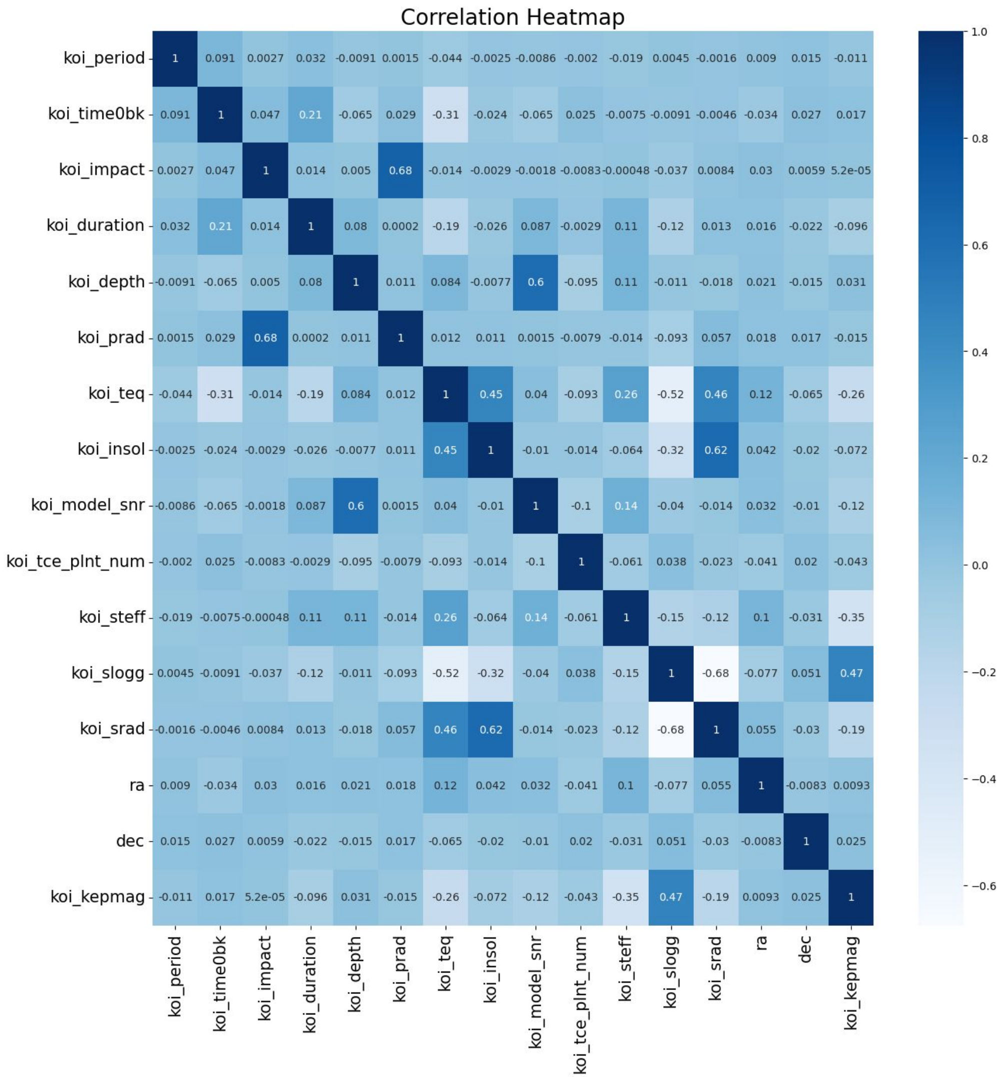
Correlation Analysis

- The initial correlation plot showed that nearly all of the error features had ±0.99-±1.00 correlation with the feature.
  - This makes sense as the error should increase proportionally with the measurement.
- As a result, we removed the error columns.
- Right shows the correlation map without error columns.



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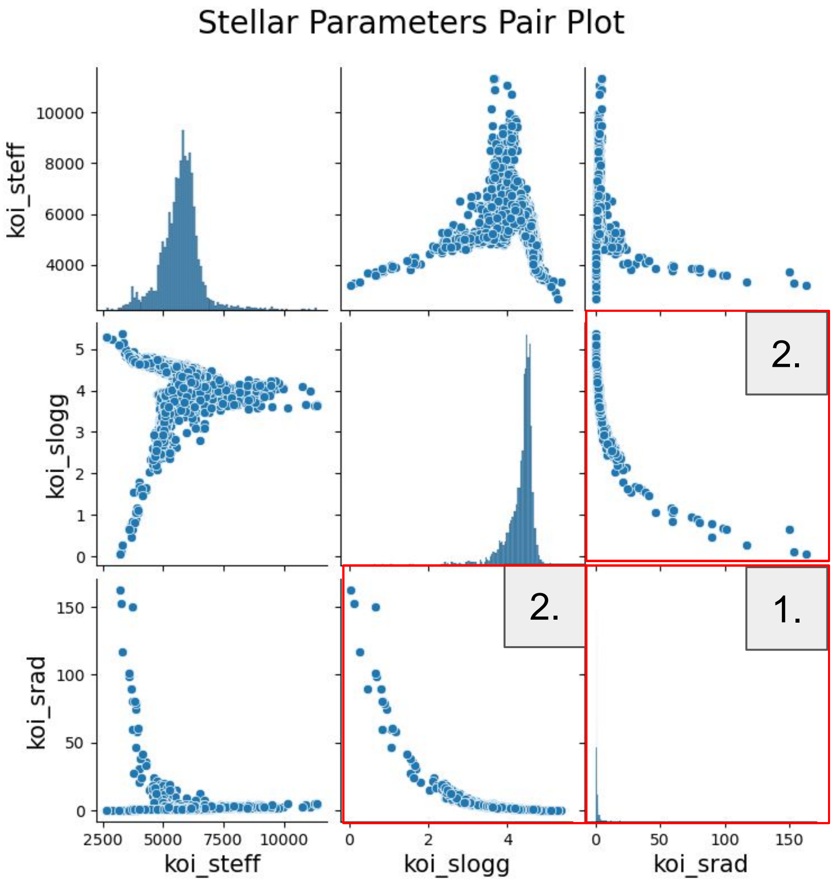
Pair Plot

- Created pairplots to review distributions of features.
  - Due to large number of features, we grouped them based on the categories of features (stellar parameter features, TCE features, and transit property features).
- Some common patterns amongst features:

1. **Most were heavily right skewed, with large outliers.**
2. **There were four features that displayed exponential/logarithmic growth/decay.**

- As a result, we decided to log transform all of our numeric features and re-evaluate them.



Log Transformed Heatmap

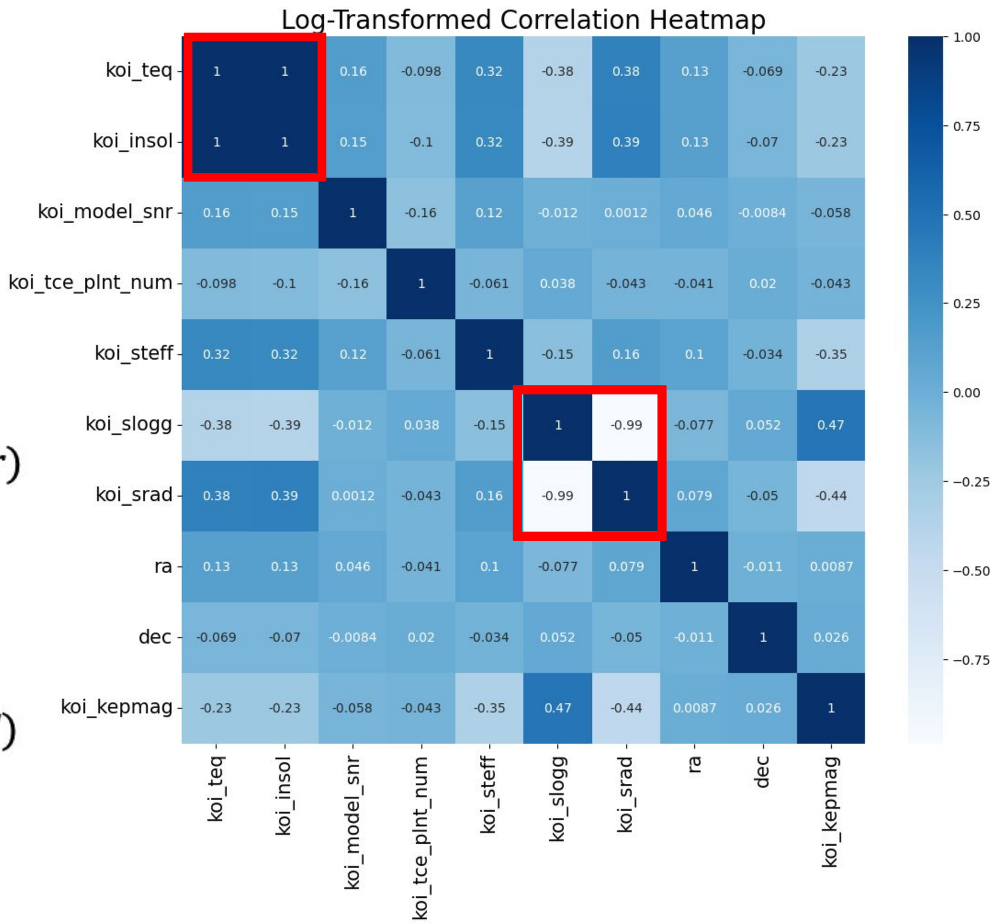
- After Log Transformation, we saw collinearity with 4 features: koi_teq and koi_insol, koi_slogg and koi_srad.
- koi_slogg is the gravitational acceleration of the star and koi_srad is the radius of the star.

$$g = \frac{GM}{r^2} \longrightarrow \log(g) = \log(GM) - 2\log(r)$$

- koi_teq is the equilibrium temperature of the object and koi_insol is the heat flux.

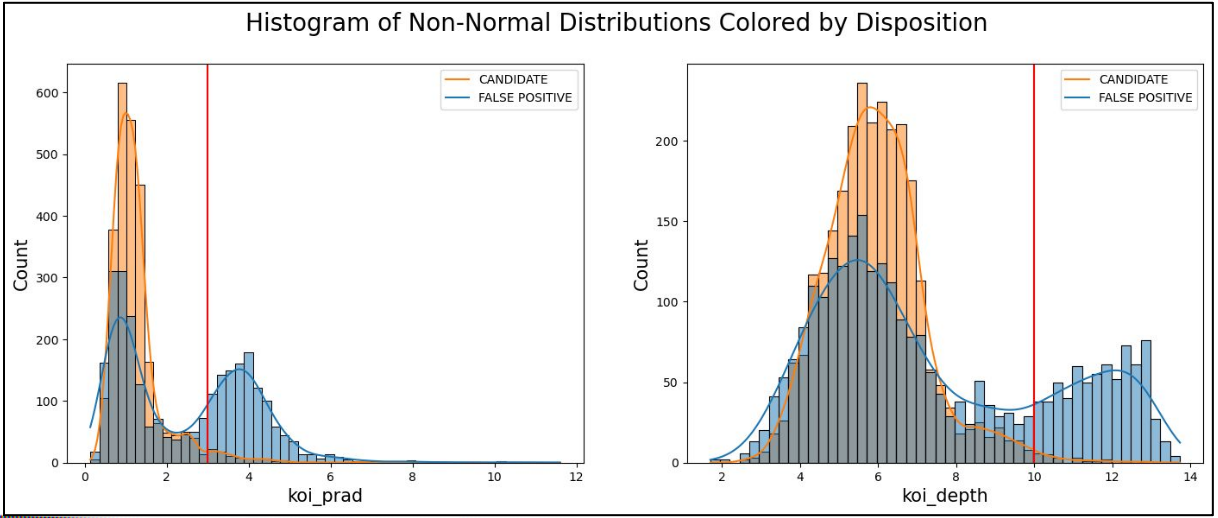
$$q = \sigma\varepsilon T^4 \longrightarrow \log(q) = \log(\sigma\varepsilon) + 4\log(T)$$

- We removed koi_srad and koi_insol to avoid collinearity and redundancy.



Bimodal Distributions

- We observed some bimodal distributions for several of our features and we attempted to bin the features such that the the peaks were in their own bin.
  - Red line is where we set the bin boundaries.
- However, it led to ~1-2% decrease in accuracy for our models, so we did not go down this route.



Missing Values, Scaling & Categorical Values

Missing Values:

- Calculated percentage of missing values
- Dropped rows with missing values in astronomical features (~%4 of data in train, ~3% in validation, ~2% in test)
    - Transit properties (koi_impact, koi_teq)
    - Stellar parameters (koi_steff, koi_slogg, koi_srad)
    - Other (koi_model_snr, koi_tce_plnt_num, koi_tce_delivname)

Scaling:

- Applied log transform to transit properties and specific features
- RobustScaler for numeric columns to handle outliers
- Binned features for non-normal distributions

Missing Values, Scaling & Categorical Values (cont.)

Categorical Values:

- Binary encoded target (Candidate:1, False Positive: 0)
- One-hot encoding categorical variables
    - Koi_tce_delivname (3 categories)
    - Koi_tce_plnt_num (7 categories)

All transformations were applied consistently across train/validation/test sets*

Baseline Model

- We began with exploring a logistic regression model as our baseline
  - Simple linear classifier
  - 5-fold cross validation to assess performance
  - Default parameters
- As a second iteration to our baseline model, we ran a random forest model
  - 500 trees, 5-fold cross validation

Can we improve these with a neural network?

Baseline Model

We will start with a baseline model our more complicated model will compare. We will use a logistic regression as our baseline.

```python
# create logistic regression model
linear_model = LogisticRegression(max_iter=1000)
linear_model.fit(X_train_final, y_train_final)


# use cross validation for determining scores
cv_scores = cross_val_score(linear_model, X_train_final, y_train_final, cv=5)

print('Scores;', cv_scores)
print('Mean Score:', np.mean(cv_scores))

val_pred_lr = linear_model.predict(X_val_final)
val_accuracy_lr = accuracy_score(y_val_final, val_pred_lr)
print('Validation Accuracy:', val_accuracy_lr)
```

✓ 0.2s

```
Scores; [0.80934579 0.80373832 0.8046729  0.81775701 0.78785047]
Mean Score: 0.8046728971962617
Validation Accuracy: 0.8053691275167785
```

Random Forest Model

```python
rf_model = RandomForestClassifier(n_estimators=500)

rf_model.fit(X_train_final, y_train_final)

rf_cv_scores = cross_val_score(rf_model, X_train_final, y_train_final, cv=5)

print('Scores:', rf_cv_scores)
print('Mean Score:', np.mean(rf_cv_scores))

# Validation accuracy
val_pred_rf = rf_model.predict(X_val_final)
val_accuracy_rf = accuracy_score(y_val_final, val_pred_rf)
print('Validation Accuracy:', val_accuracy_rf)
```

✓ 15.1s

```
Scores: [0.8411215  0.8364486  0.84205607 0.85046729 0.82429907]
Mean Score: 0.8388785046728972
Validation Accuracy: 0.8501118568232662
```

Baseline Model Metrics

Logistic Regression Metrics:

CV Scores:
[0.809 0.803 0.804 0.81775701 0.787]
Mean CV Score: 0.804
Validation Accuracy: 0.805

Random Forest Model Metrics:

CV Scores:
[0.841 0.836 0.842 0.850 0.8242]
Mean CV Score: 0.838
Validation Accuracy: 0.835

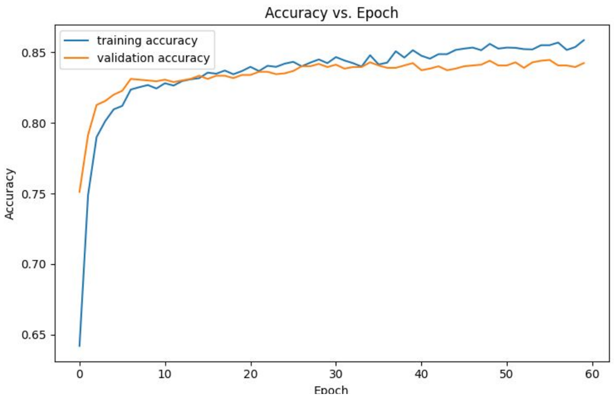
Final Model: Neural Network

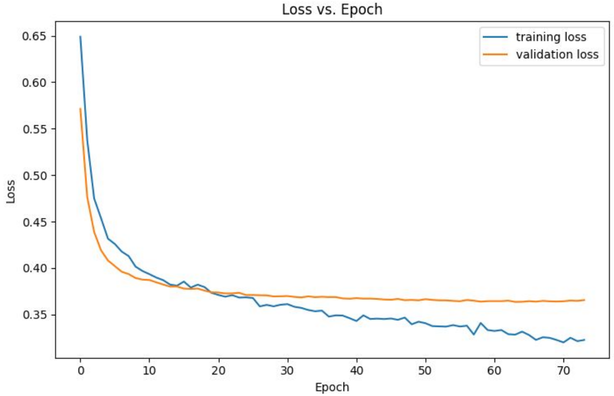
Why we chose a neural network

- Theoretically could capture more complex relationships with our dataset.
- More flexibility in tuning the model.
- Ultimately would scale better with more data.
- Achieved higher accuracy on training and validation sets.

Final validation accuracy: **0.842**

Log. Regression / RFC baseline: **0.804 / 0.835**





Neural Network Hyperparameter Selection

Neural Network Structure:

- **Input Layer:** 24 features
- **4 Dense Hidden Layers:** 256, 128, 64, 32 Neurons
- **3 Dropout Layers:** dropout rate = 0.3 for regularization
- **Output Layer:** Softmax activation

Other Hyperparameters:

- **Learning Rate:** 1e-5
- **Batch Size:** 32
- **Optimizer:** Adam
- **Activation Functions:** ReLU
- **# Epochs:** 1000 (with EarlyStopping callback)

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 24)	0
dense (Dense)	(None, 256)	6,400
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 128)	32,896
dropout_1 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 64)	8,256
dropout_2 (Dropout)	(None, 64)	0
dense_3 (Dense)	(None, 32)	2,080
dense_4 (Dense)	(None, 1)	33

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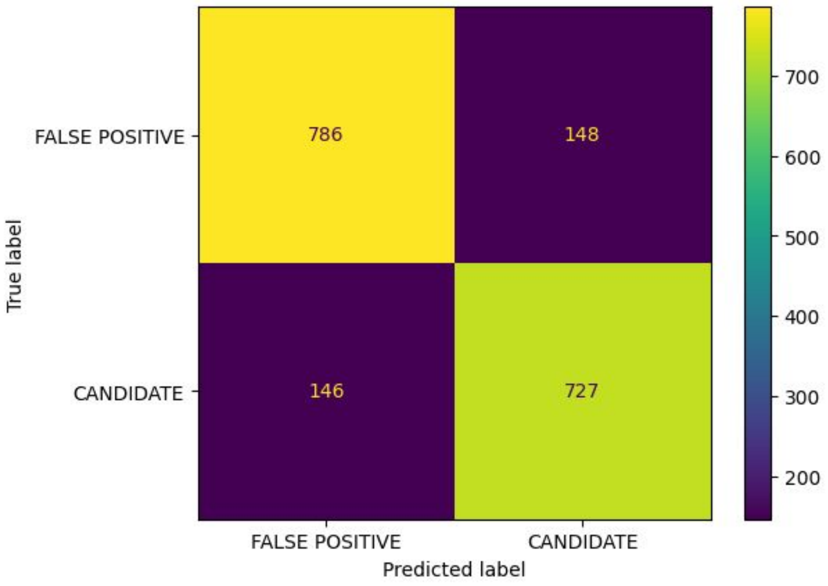
Model Evaluation

Final test accuracy: 83.7% (compared to 84% validation score)

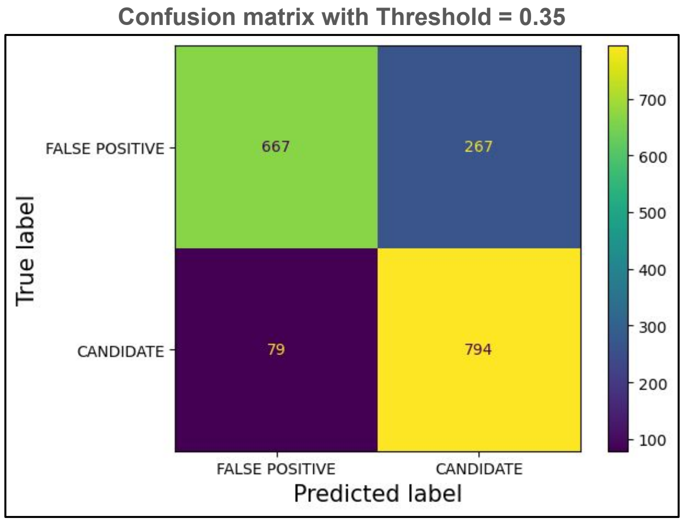
- We see good generalization from training to test.
- Consistent performance across classes.

	Precision	Recall	F1-score
False Positive	0.84	0.84	0.84
Candidate	0.83	0.83	0.83

Confusion matrix w/ threshold 0.5



Threshold Impact on Metrics



Metrics	Threshold = 0.5	Threshold = 0.35
Accuracy	0.84	**0.81**
Candidate Precision	0.82	0.75
Candidate Recall	0.82	**0.91**
False Positive Precision	0.83	**0.89**
False Positive Recall	0.83	0.71

Conclusion

- Summary
  - Started with baseline logistic regression + random forest
  - EDA + feature engineering
  - Final model selection + evaluation
  - Threshold impact on metrics
- Final model
  - Increase in test accuracy by ~1-4%from baseline model
  - Random forest performance comparable to NN
  - Good generalization - similar metrics on train/test set
- Next steps:
  - Better understanding of NASA's original classification methods
  - Better feature engineering
  - More time spent understanding each column

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References

Bilogur, Aleksey, and NASA. “Kepler Exoplanet Search Results.” Kaggle, Google LLC, 10 Oct. 2017, www.kaggle.com/datasets/nasa/kepler-exoplanet-search-results.

NASA Exoplanet Archive. NASA, exoplanetarchive.ipac.caltech.edu/docs/API_kepcandidate_columns.html. Accessed 20 Oct. 2024.

Contributions

- Victoria Brendel: Baseline logistic regression model, background and motivation, data source/structure, conclusion
- Kenneth Hahn: EDA, feature engineering, hyperparameter selection, and threshold optimization
- Moez Hudda: Missing, Categorical & Scaling. Baseline Model
- Matthew Paterno: Training, hyperparameter optimization, final model evaluation

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