Stock Market Prediction with LSTM

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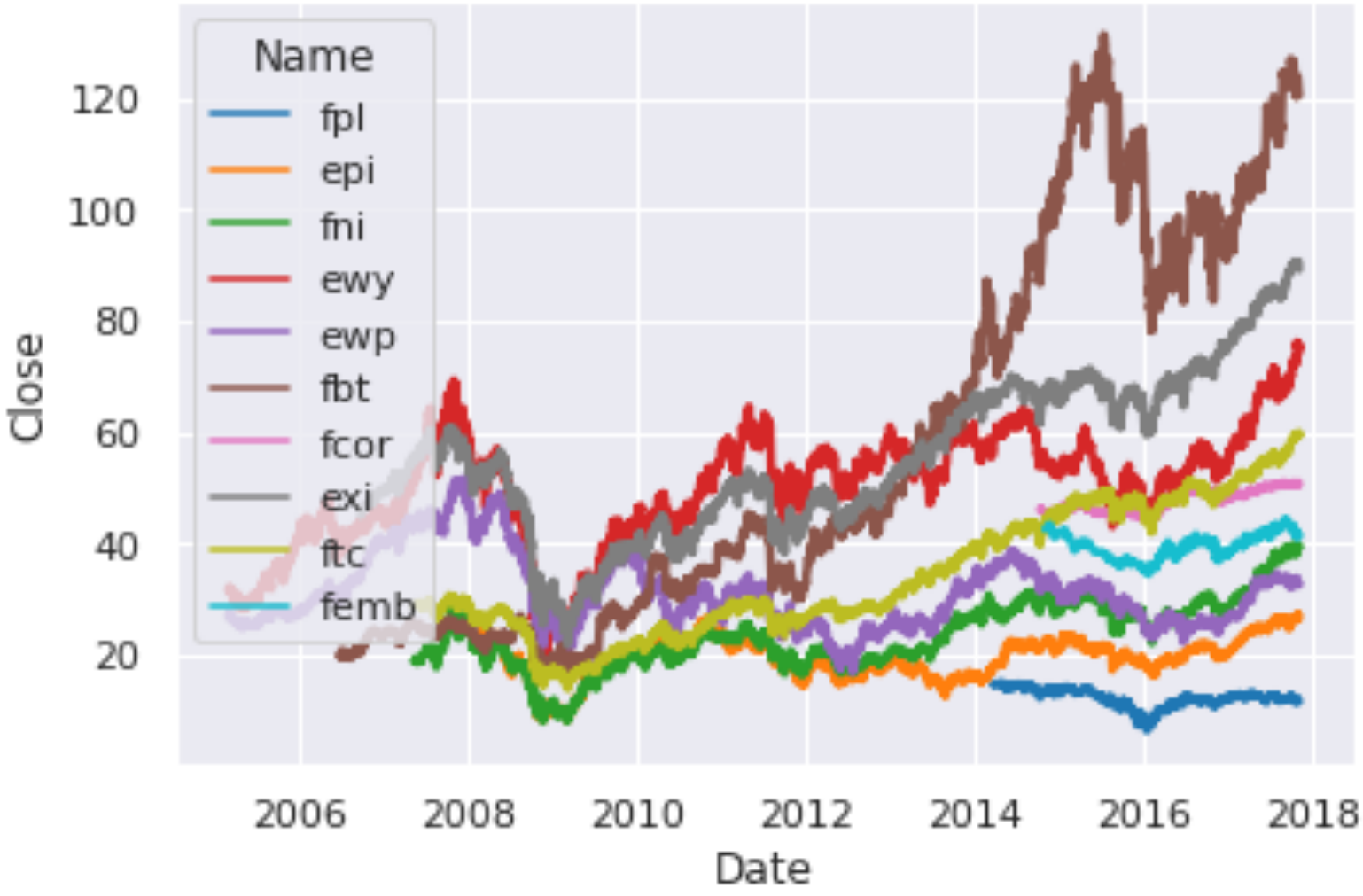
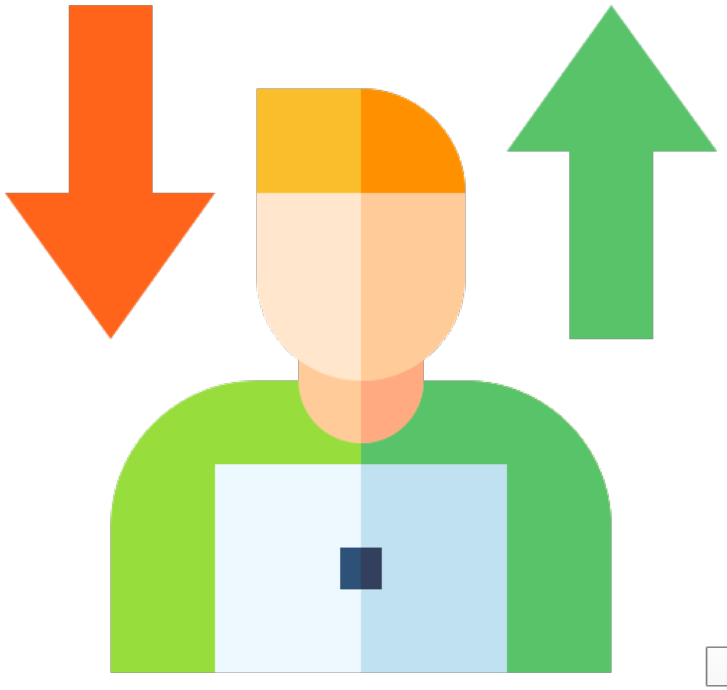
What is the problem?

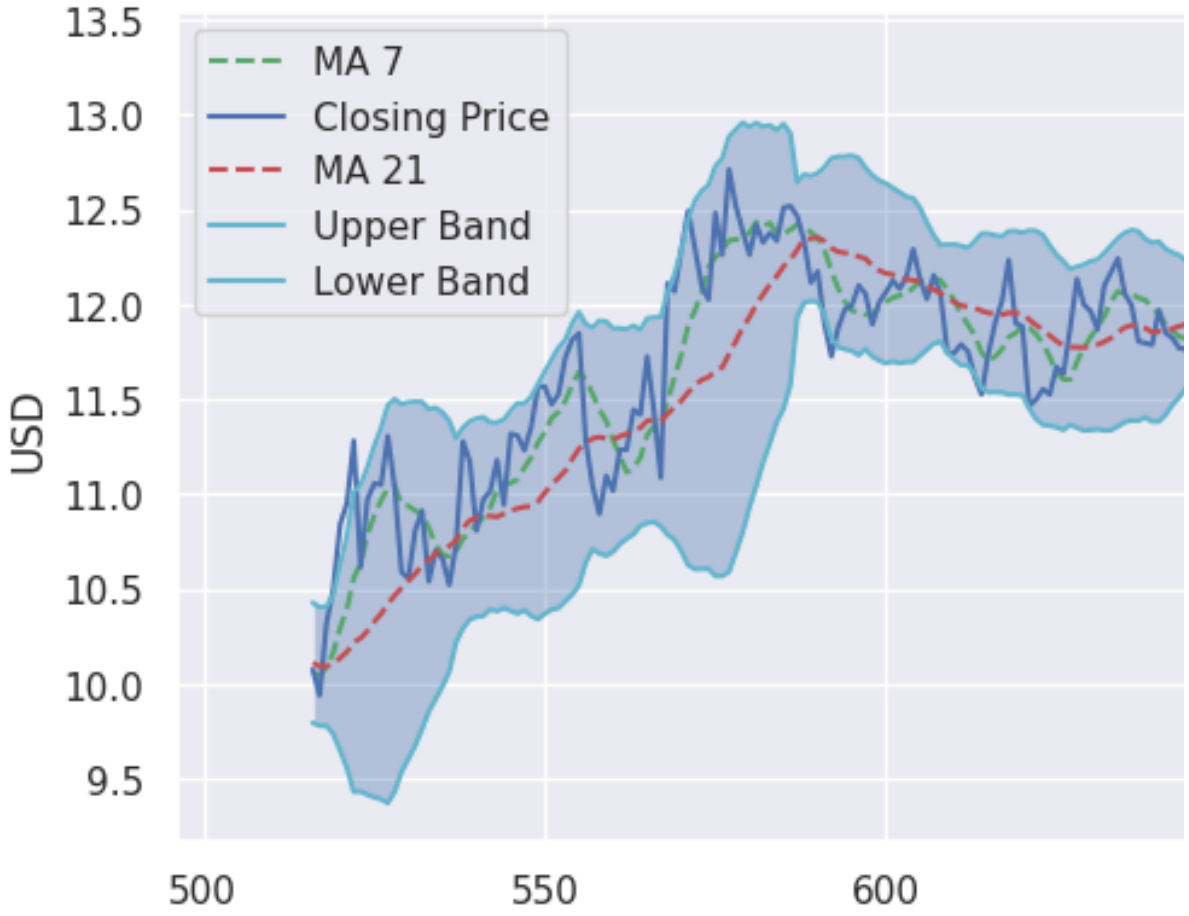


What is the problem?

Train a LSTM neural network to predict if a stock will move up or down



```
# Add the label class based on whether stock goes up or down
def add_label(df):
    idx = len(df.columns)
    new_col = np.where(df['Close'] >= df['Close'].shift(1), 1, 0)
    df.insert(loc=idx, column='Label', value=new_col)
    df = df.fillna(0)
```



What is the problem?

Task:
Supervised learning

Performance Measure:
Validation Accuracy

Learning Component:
Technical Indicators

kaggle

```
df_etfs.head()
```

	Date	Open	High	Low	Close	Volume	OpenInt	Name
0	2014-03-27	14.705	14.795	14.698	14.729	698621	0	fpl
1	2014-03-28	14.890	14.890	14.729	14.729	164979	0	fpl
2	2014-03-31	14.839	14.948	14.729	14.876	86108	0	fpl
3	2014-04-01	14.948	14.948	14.729	14.729	169637	0	fpl
4	2014-04-02	14.737	14.755	14.713	14.747	110332	0	fpl

Data Background

NASDAQ stocks and ETFs

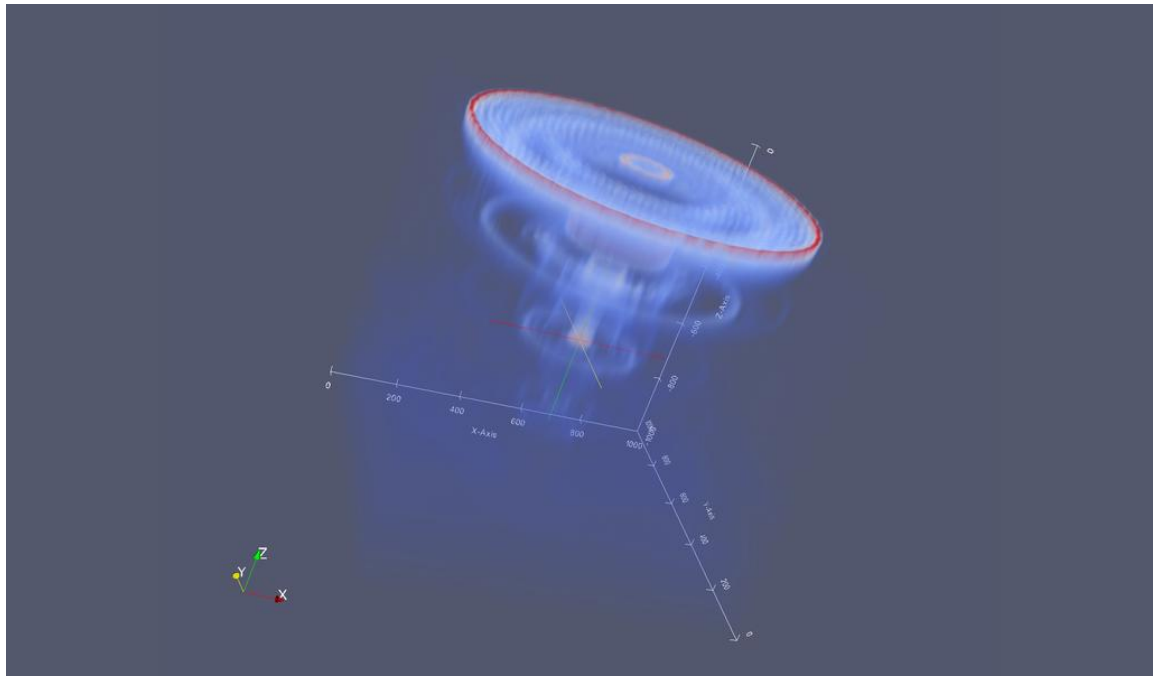
Historical data up until 04/01/2020

Data Size: 3GB

Why is it an important problem?

Motivation

- Lab research
- Career
- Personal interest



Related work

Literature Review

- Many articles cover implementing hybrid ML models. Not the most helpful for a limited scope class project
- Books, API documentation, and Keras tutorial examples so far have been the most helpful for both understanding and implementing concepts

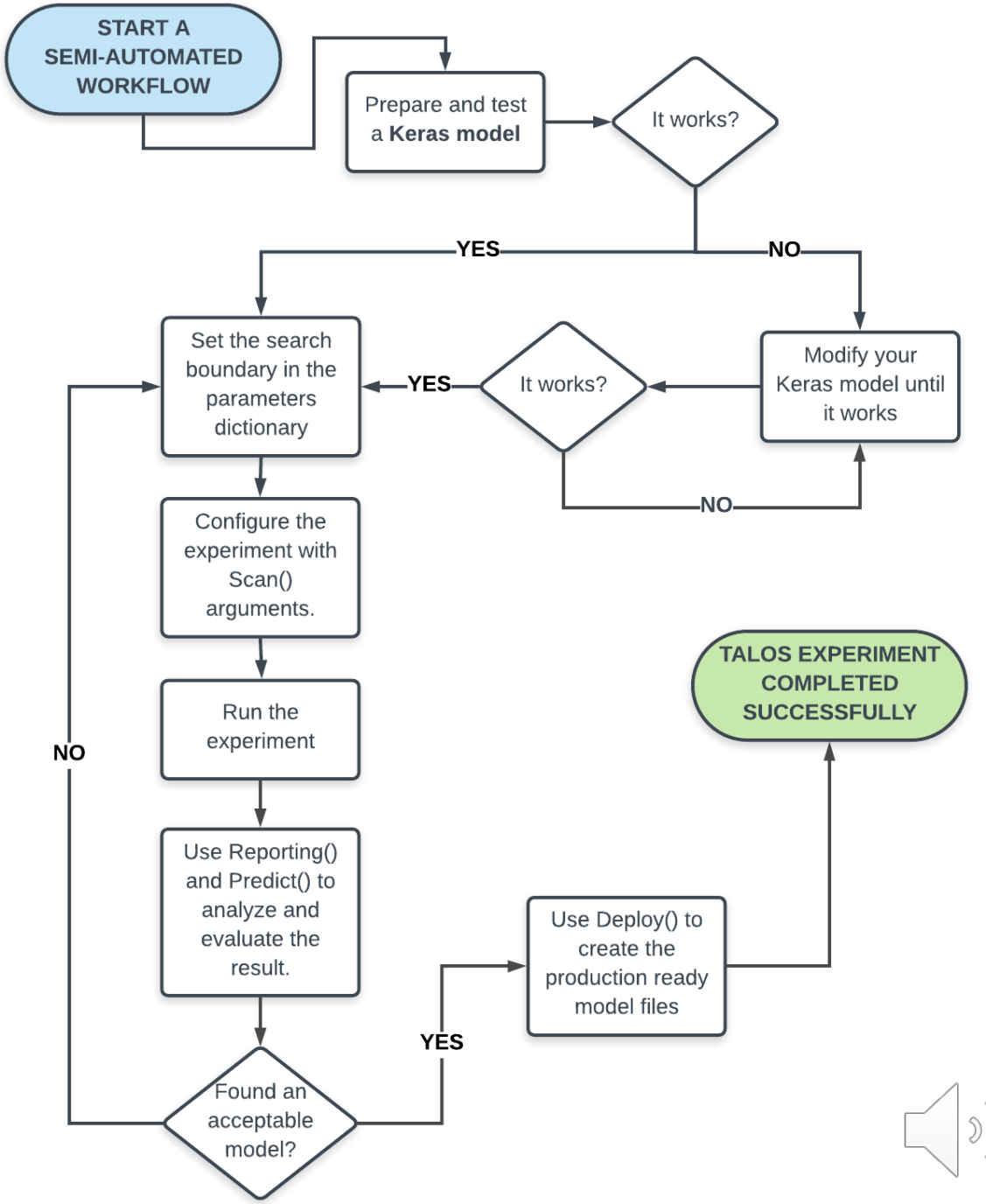
Techniques chosen and why

Techniques to tackle problem

- Feature creation
- Data imputation
- Data normalization
- Automated hyper-parameter tuning

```
df_ti = df_ti.fillna(df_ti.median())
```

```
def normalized_df(df):
    normalized_df=(df-df.mean())/df.std()
    return normalized_df
```



```
p = {'lr': (0.0001, 0.001, 0.005, 0.05, 0.01),
     'first_neuron': [8, 16, 32, 64],
     'epochs': [5, 10, 15, 20, 30, 40, 50],
     'optimizer': ['Adam', 'SGD', 'RMSprop'],
     'losses': ['binary_crossentropy']}
```

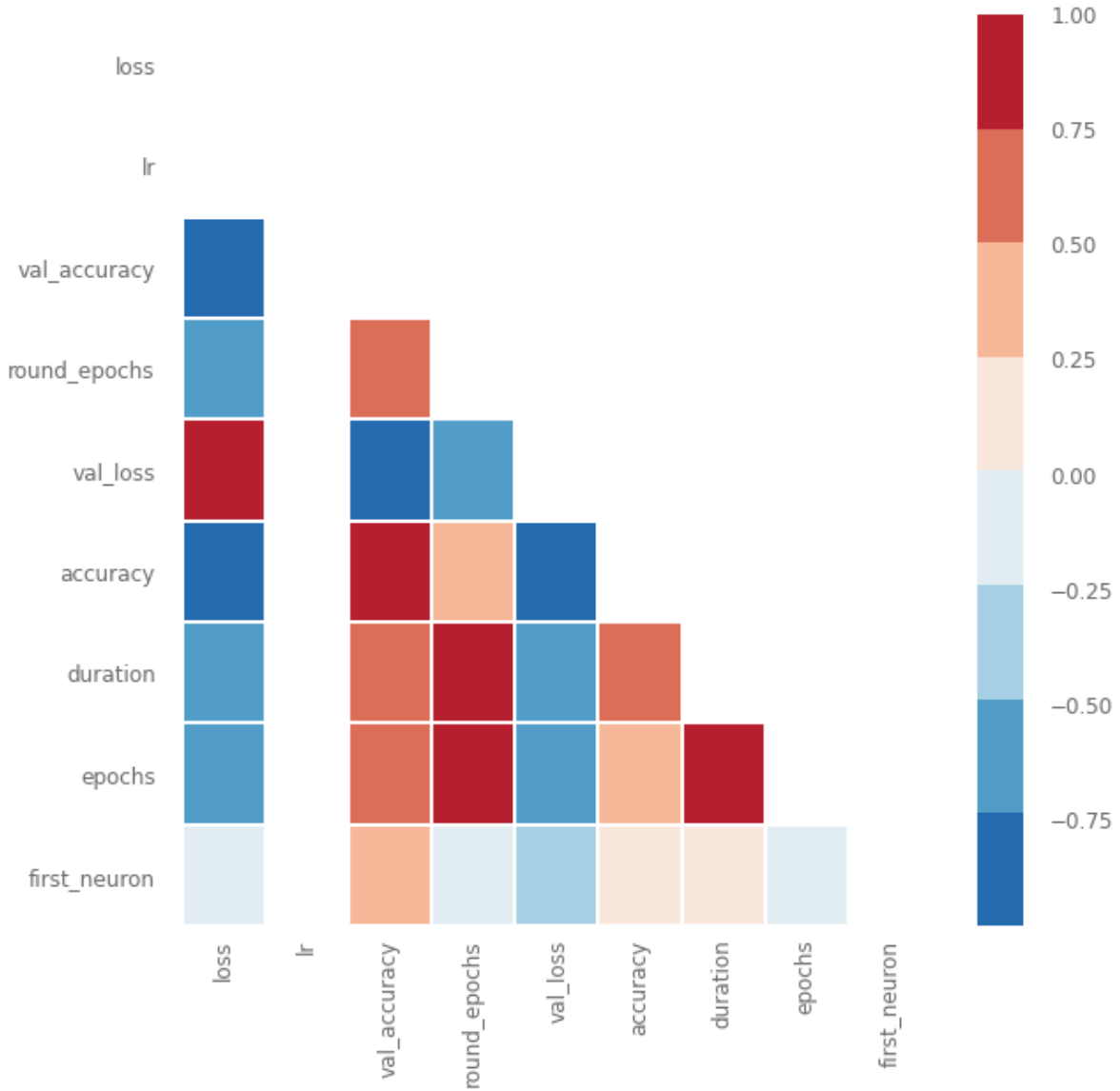
```
def build_lstm(X_train, y_train, X_test, y_test, params):
  inputs = keras.layers.Input(shape=(X_train.shape[1], X_train.shape[2]))
  lstm_out = keras.layers.LSTM(params['first_neuron'])(inputs)
  outputs = keras.layers.Dense(1)(lstm_out)
  model = keras.Model(inputs=inputs, outputs=outputs)

  model.compile(optimizer=params['optimizer'],
                loss=params['losses'],
                metrics=['accuracy'])
  history = model.fit(x=X_train, y=y_train, epochs=params['epochs'], validation_data=(X_test, y_test))
  return history, model
```

```
%time
scan_object = ta.Scan(x=X_train,
            y=y_train,
            model=build_lstm,
            params=p,
            seed=777,
            experiment_name='exp_run_1',
            x_val=X_test,
            y_val=y_test
           )
```

Talos API

- Set parameters to test
- Build model to specs
- “Scan” all parameter permutations
- “Report” each model’s performance

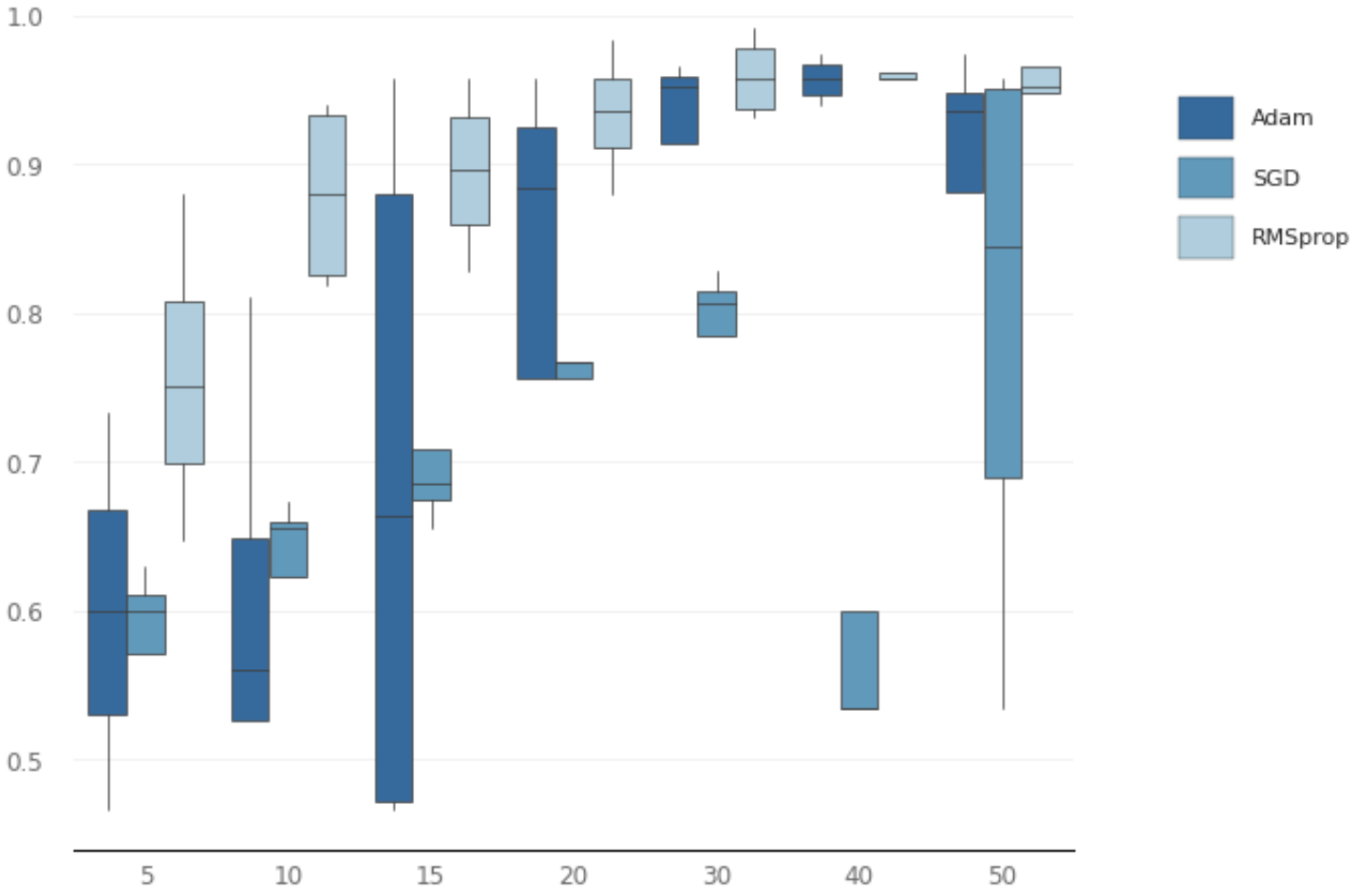
Empirical evaluation



Visualizing Relationships

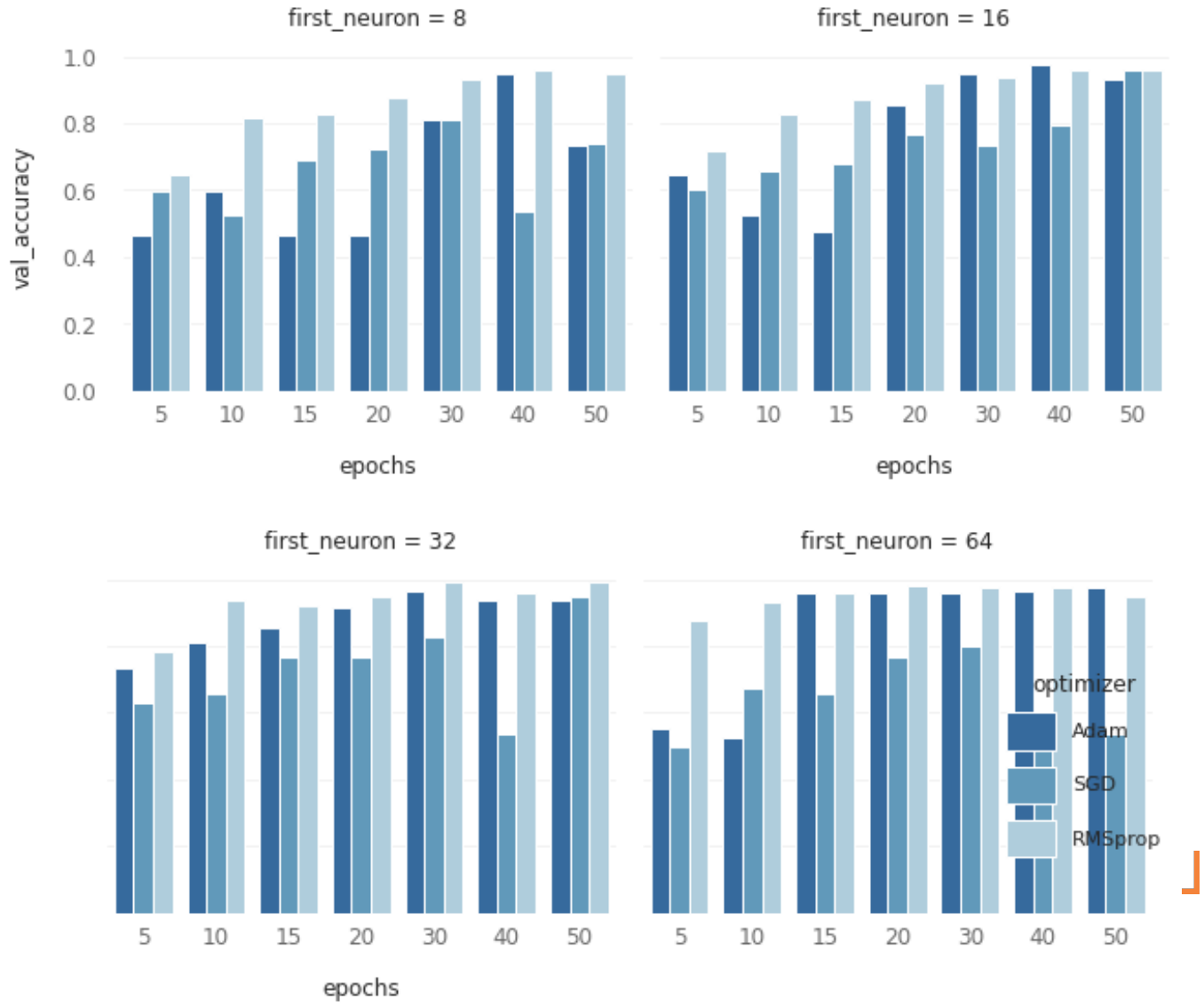
Validation Accuracy has strong, positive correlations with:

- Number of neurons
- Epochs
- Duration of training
- Round of epoch training



Validation Accuracy Distribution of Optimizers

- Overall distribution trend is logarithmic
- As epochs increase (x-axis), val acc increases
- Adam has largest variance
- RMSprop has smallest variance



4 Dimensional Bar Grid

Breaks down validation accuracy for each neuron density by epochs per each optimizer

- RMSprop performs consistently better in each neuron density
- SGD seems to struggle at highest neural density; perhaps overfitting?

Conclusion

```
# returns the highest value for validation accuracy
analyze_object.high('val_accuracy')
```

```
0.9913793206214905
```

```
# returns the number of rounds it took to find best model
analyze_object.rounds2high('val_accuracy')
```

```
56
```

Best Model

- 84 different models trained
- Best model:
- Found at round 56 of 84
- Validation accuracy: 99.14%

Round	Val Acc	LR	Epochs	Optimizer	Neural Density
56	99.14%	0.0001	50	RMSprop	32

Questions?

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