Scaling data and KNN Regression

MACHINE LEARNING FOR FINANCE IN PYTHON

Nathan George
Data Science Professor

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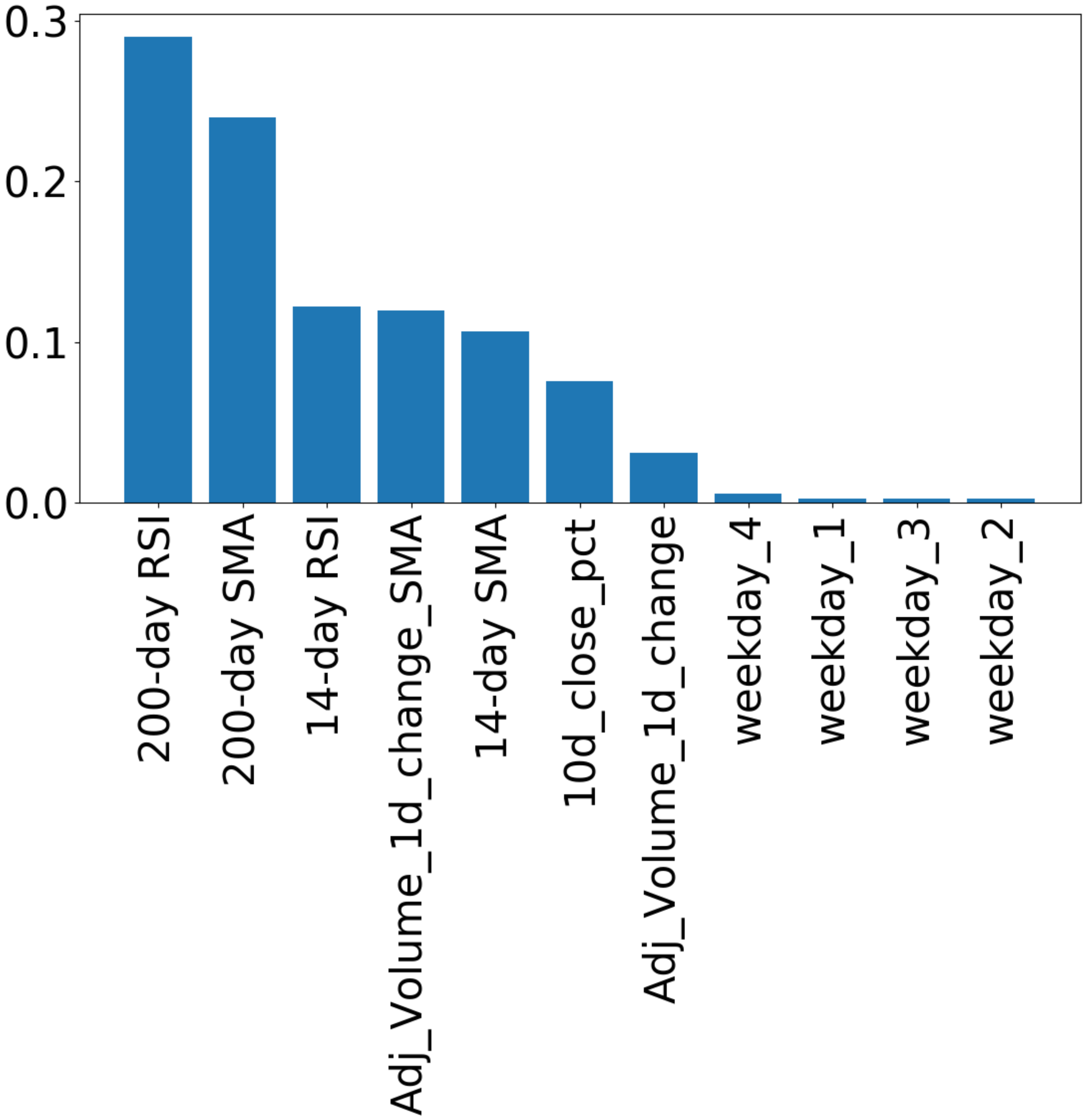

0.3
0.2
0.1
0.0
200-day RSI
200-day SMA
14-day RSI
Adj_Volume_1d_change_SMA
14-day SMA
10d_close_pct
Adj_Volume_1d_change
weekday_4
weekday_1
weekday_3
weekday_2

Feature selection: remove weekdays

```python
print(feature_names)
```

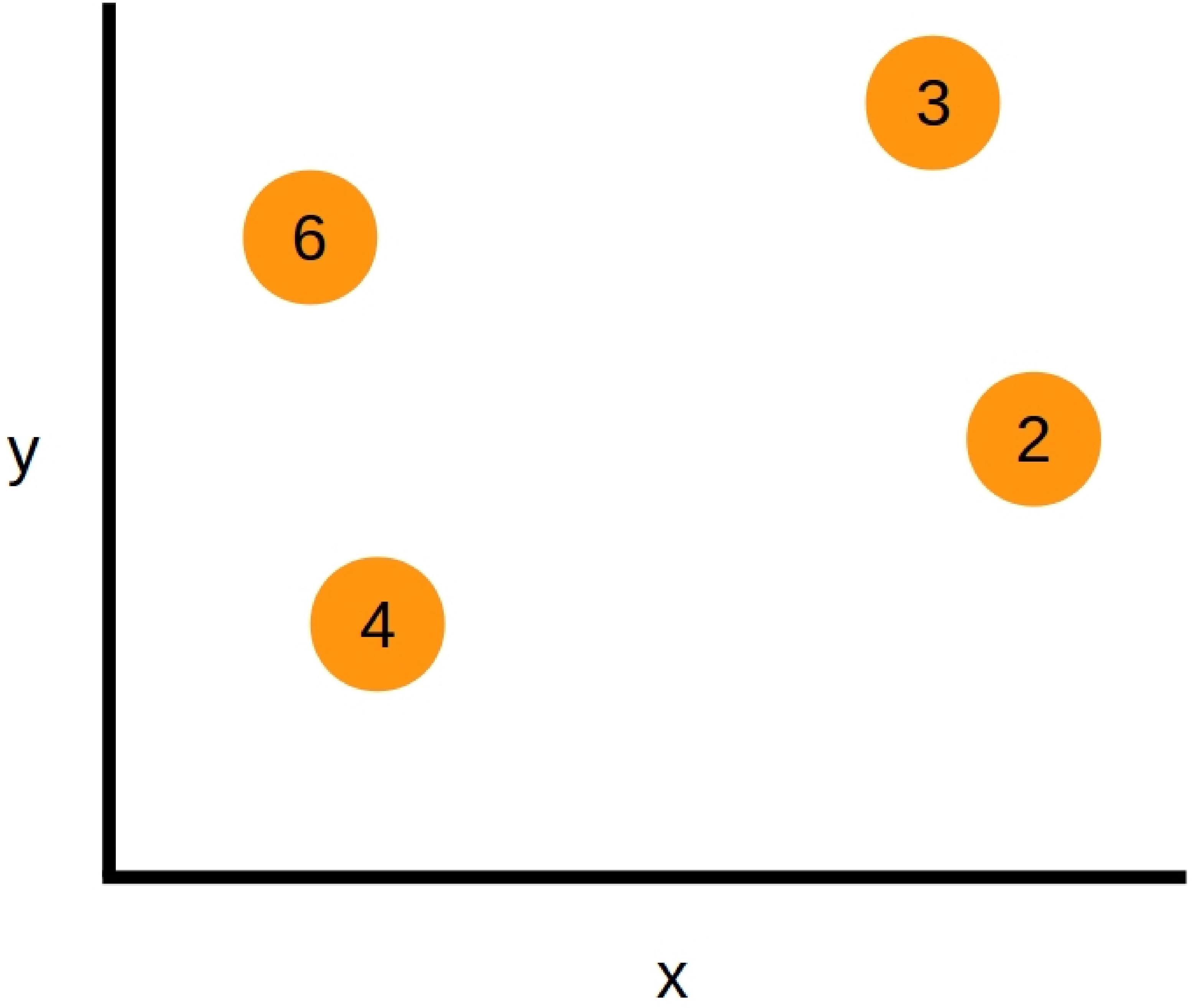
```
['10d_close_pct',
 '14-day SMA',
 '14-day RSI',
 '200-day SMA',
 '200-day RSI',
 'Adj_Volume_1d_change',
 'Adj_Volume_1d_change_SMA',
 'weekday_1',
 'weekday_2',
 'weekday_3',
 'weekday_4']
```

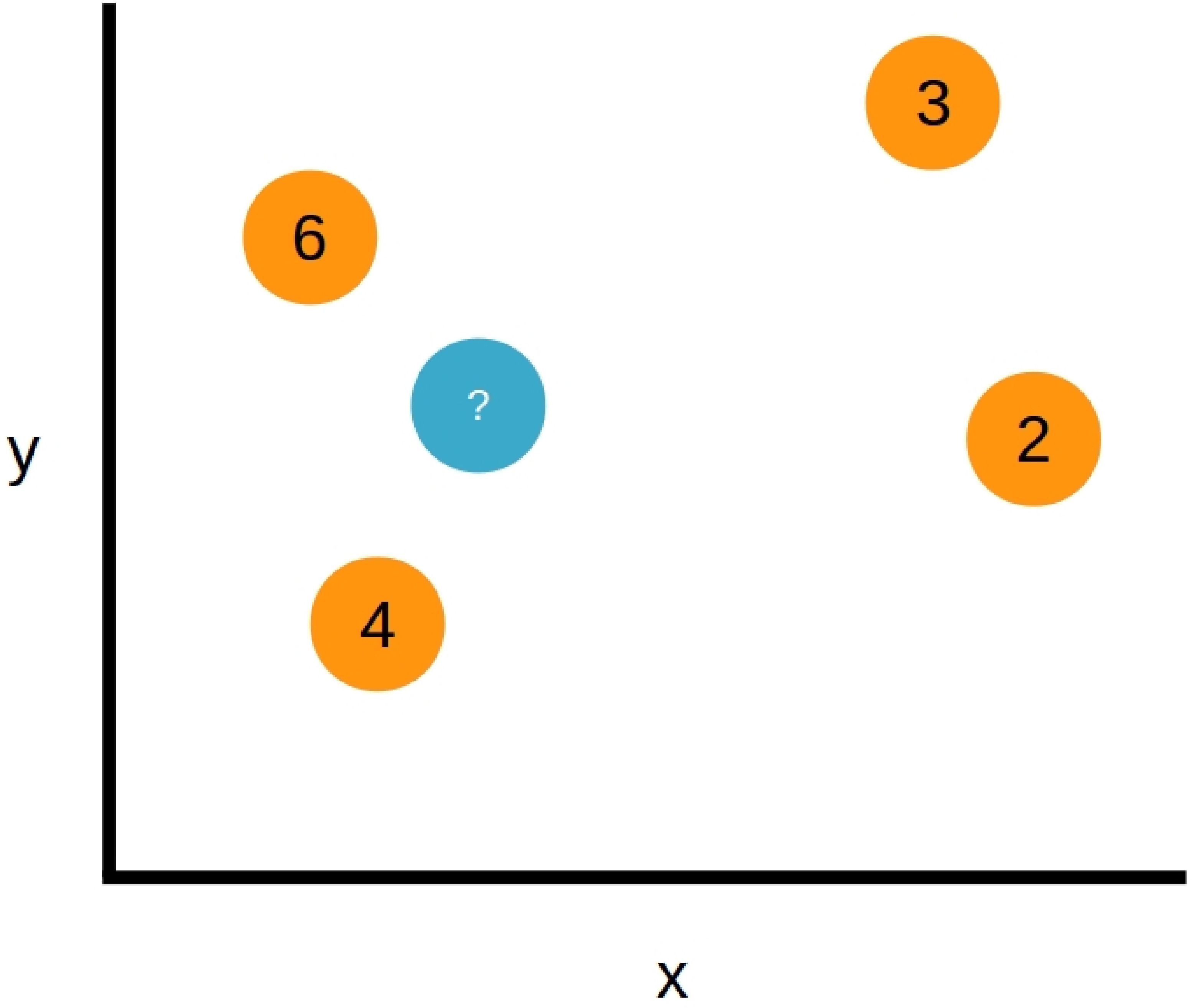
```python
print(feature_names[:-4])
```

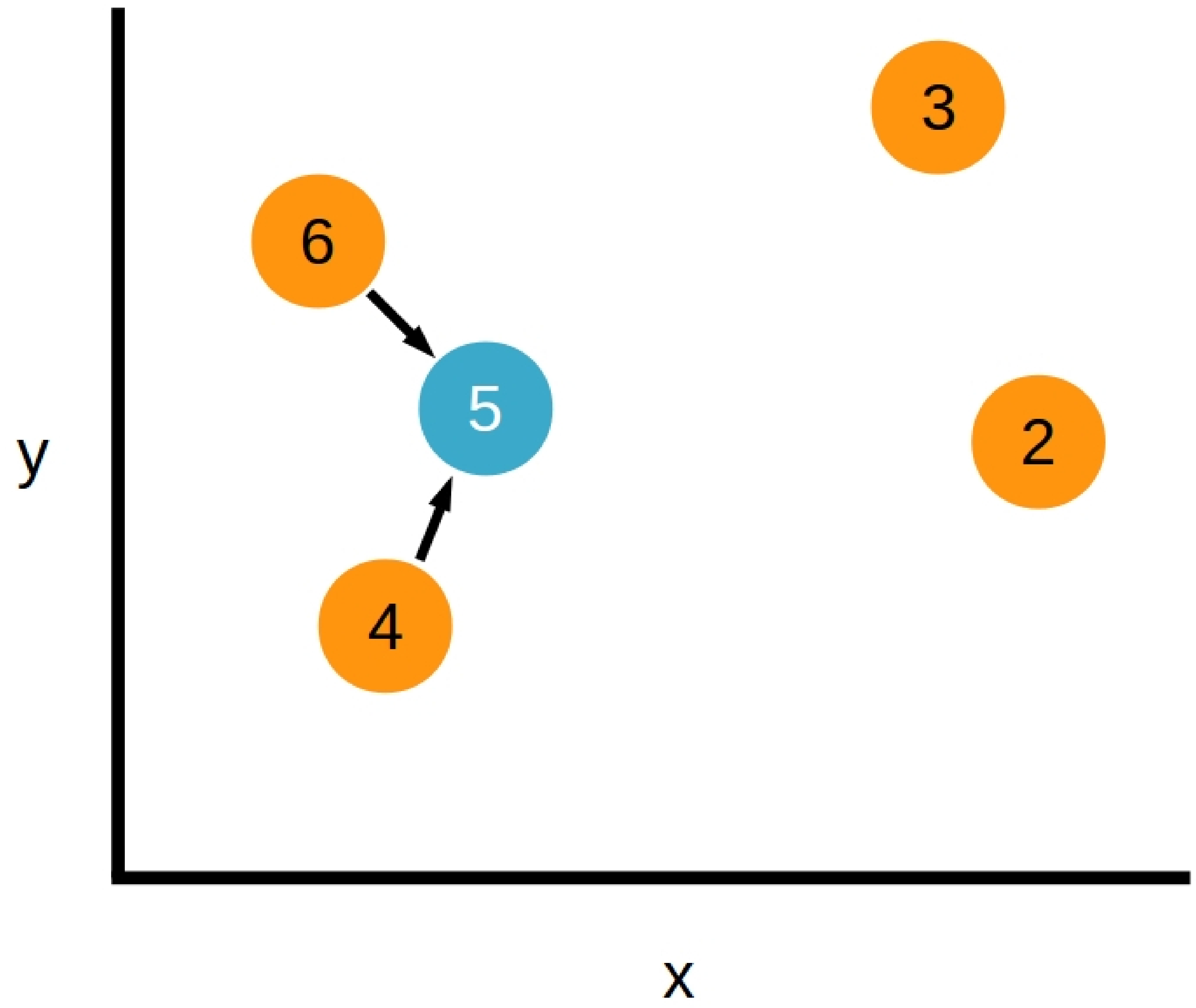
```
['10d_close_pct',
 '14-day SMA',
 '14-day RSI',
 '200-day SMA',
 '200-day RSI',
 'Adj_Volume_1d_change',
 'Adj_Volume_1d_change_SMA']
```

Remove weekdays

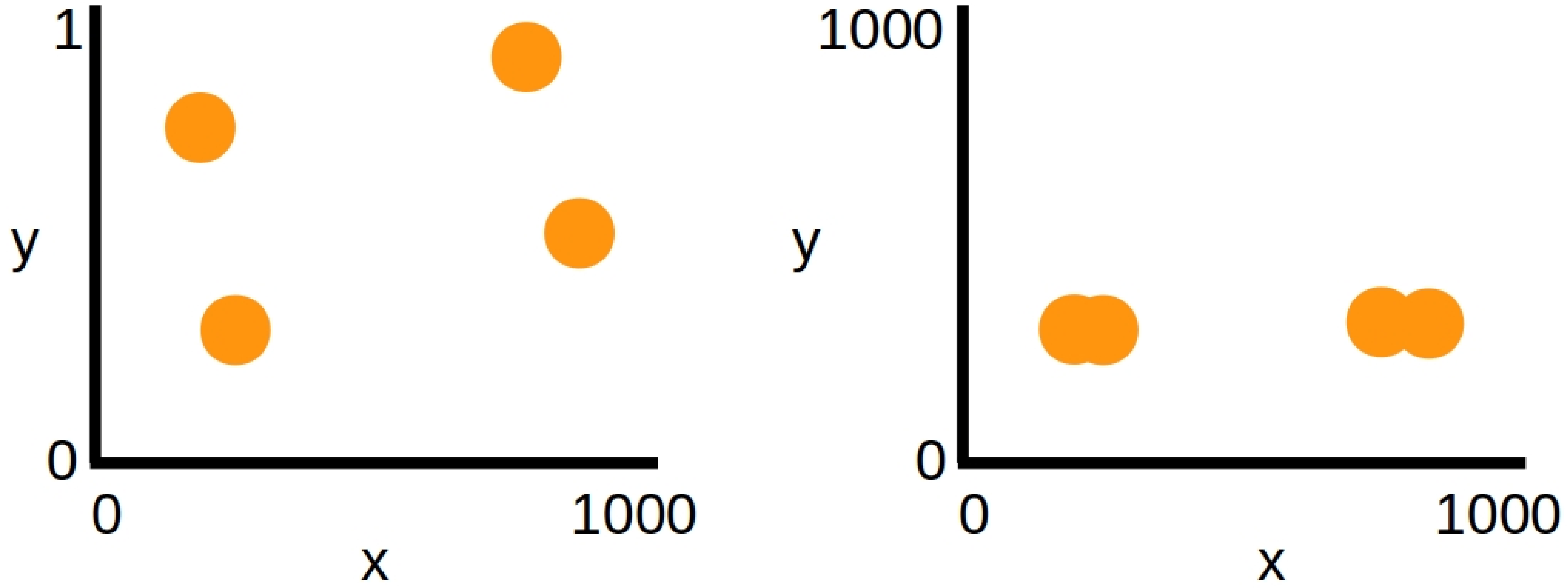
```
train_features = train_features.iloc[:, :-4]
test_features = test_features.iloc[:, :-4]
```


3
6
y
2
4
x


3
6
?
y
2
4
x


3
6
5
2
y
4
x

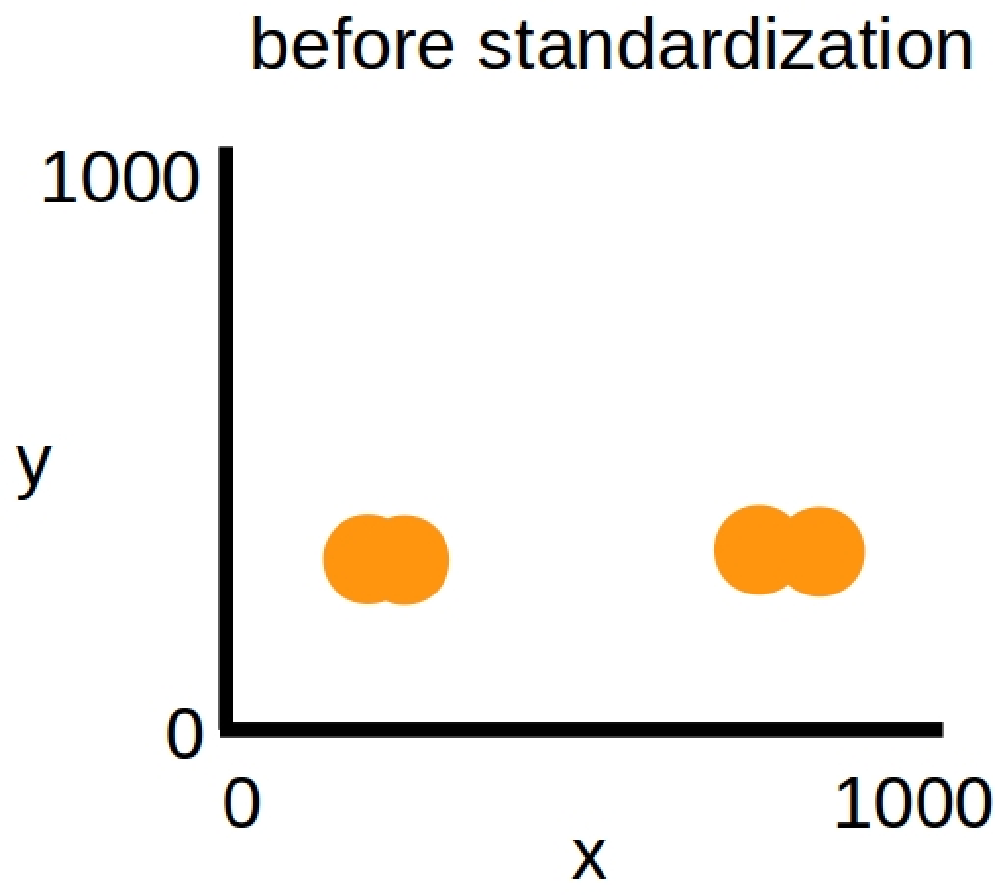
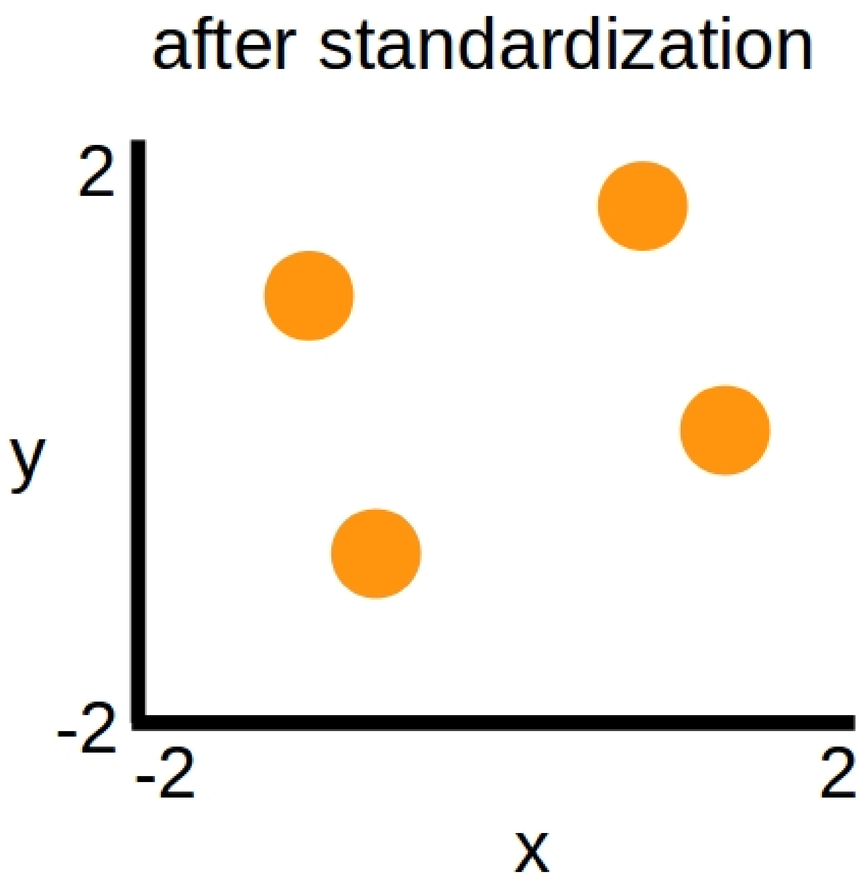
$$D(A,B)=\sum_{i}\left(\left|(a_i-b_i)\right|\right)^{(1/p)}$$


1
y
0
0
1000
x
1000
y
0
0
1000
x

Scaling options

Scaling options:

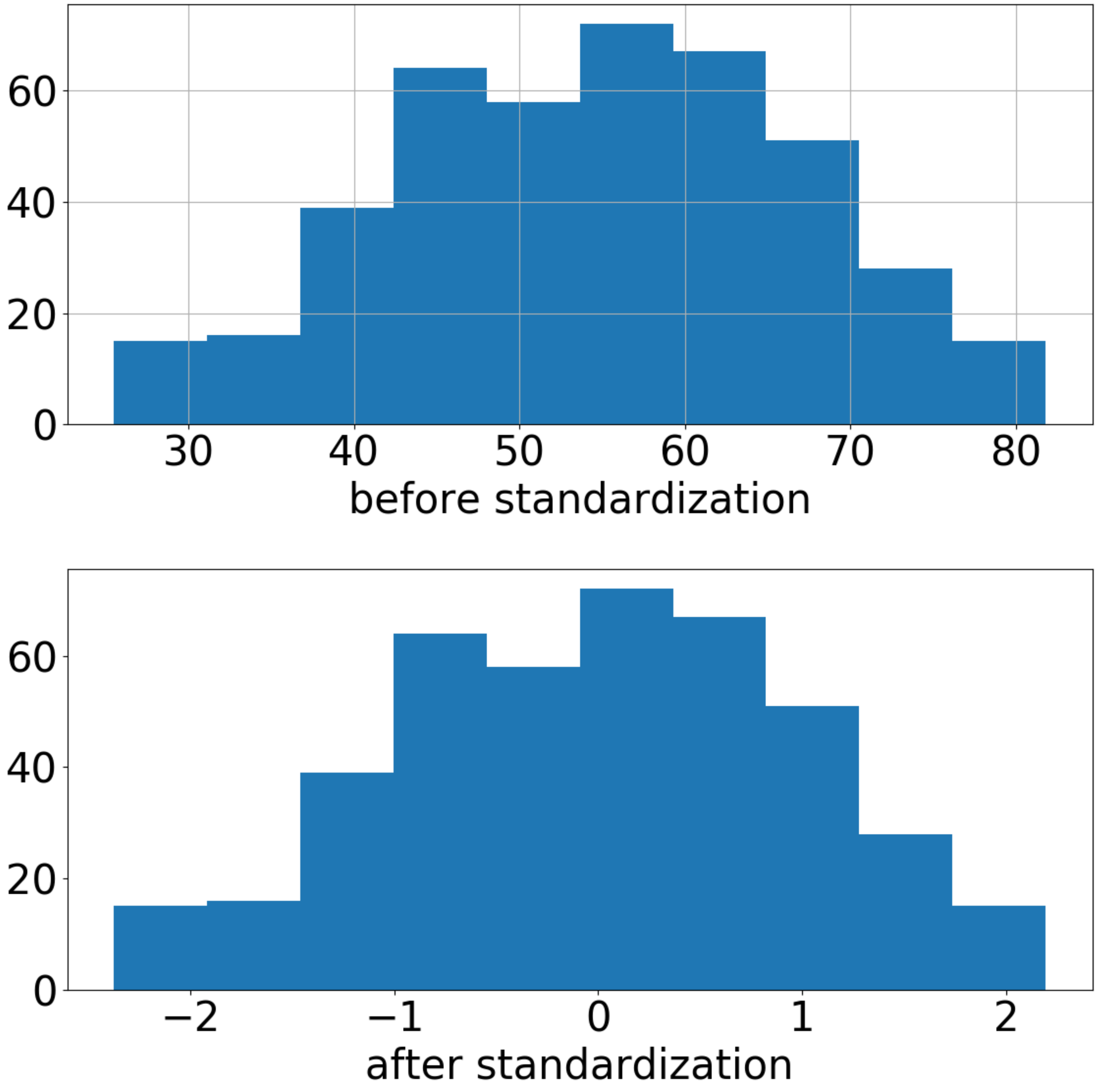
- min-max
- standardization
- median-MAD
- map to arbitrary function (e.g. sigmoid, tanh)


before standardization
1000
y
0
0
x
1000

after standardization
2
y
-2
-2
x
2

sklearn's scaler

```
from sklearn.preprocessing import scaler

sc = scaler()
scaled_train_features = sc.fit_transform(train_features)
scaled_test_features = sc.transform(test_features)
```



60
40
20
0
30
40
50
60
70
80
before standardization
60
40
20
0
−2
−1
0
1
2
after standardization

Making subplots

```
# create figure and list containing axes
f, ax = plt.subplots(nrows=2, ncols=1)
# plot histograms of before and after scaling
train_features.iloc[:, 2].hist(ax=ax[0])
ax[1].hist(scaled_train_features[:, 2])
plt.show()
```

Scale data and use KNN!

MACHINE LEARNING FOR FINANCE IN PYTHON

Neural Networks

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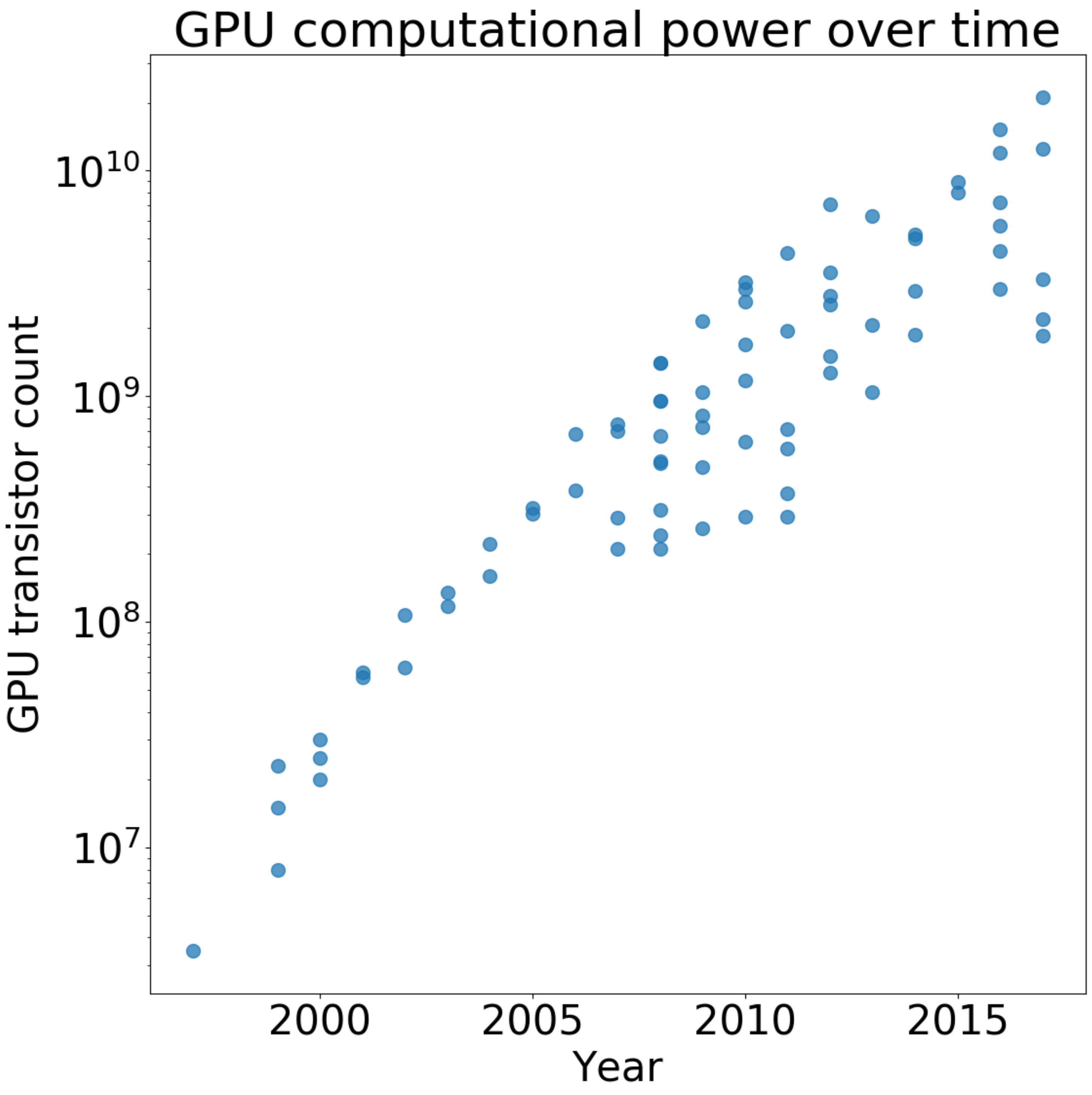
Data Science Professor

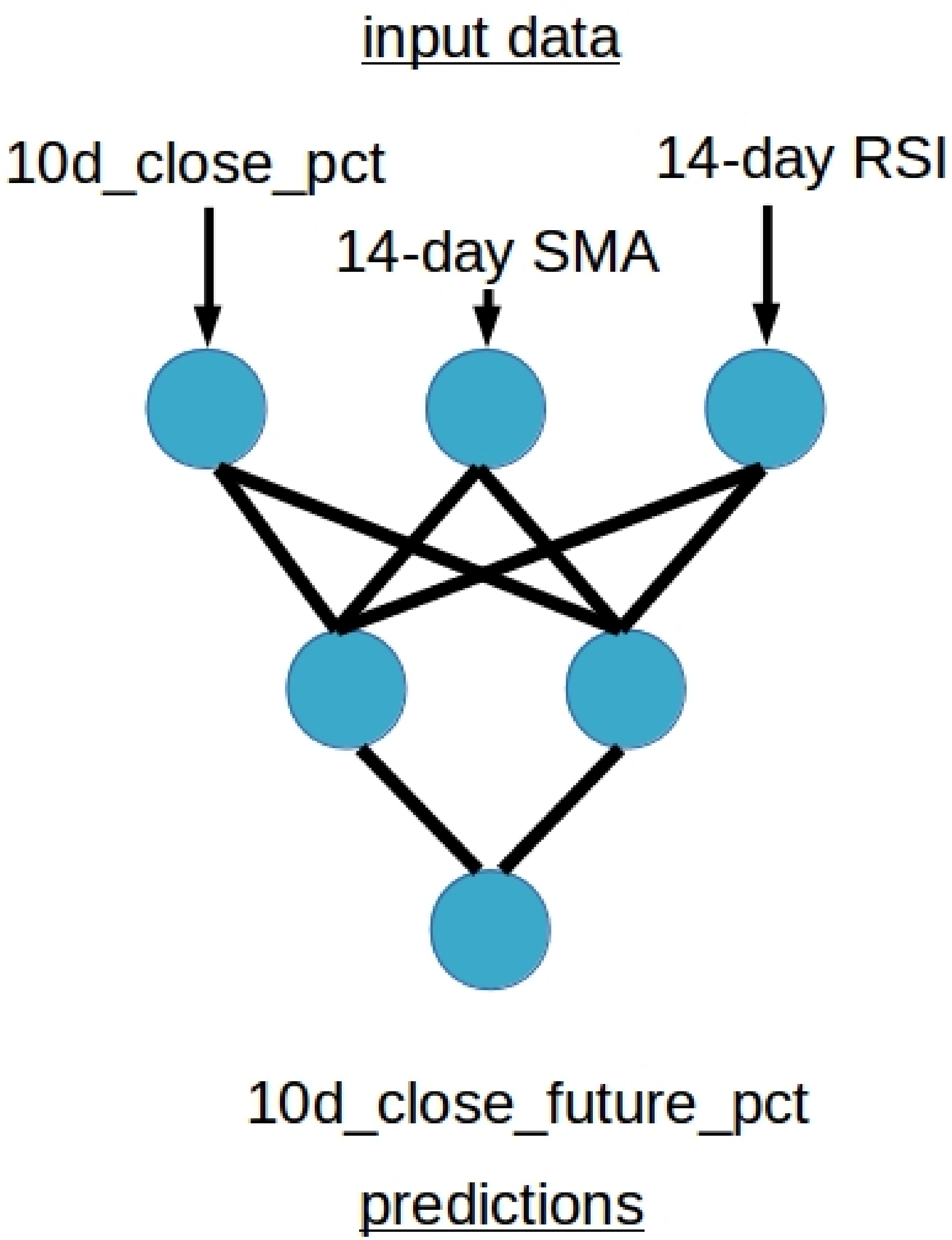
datacamp

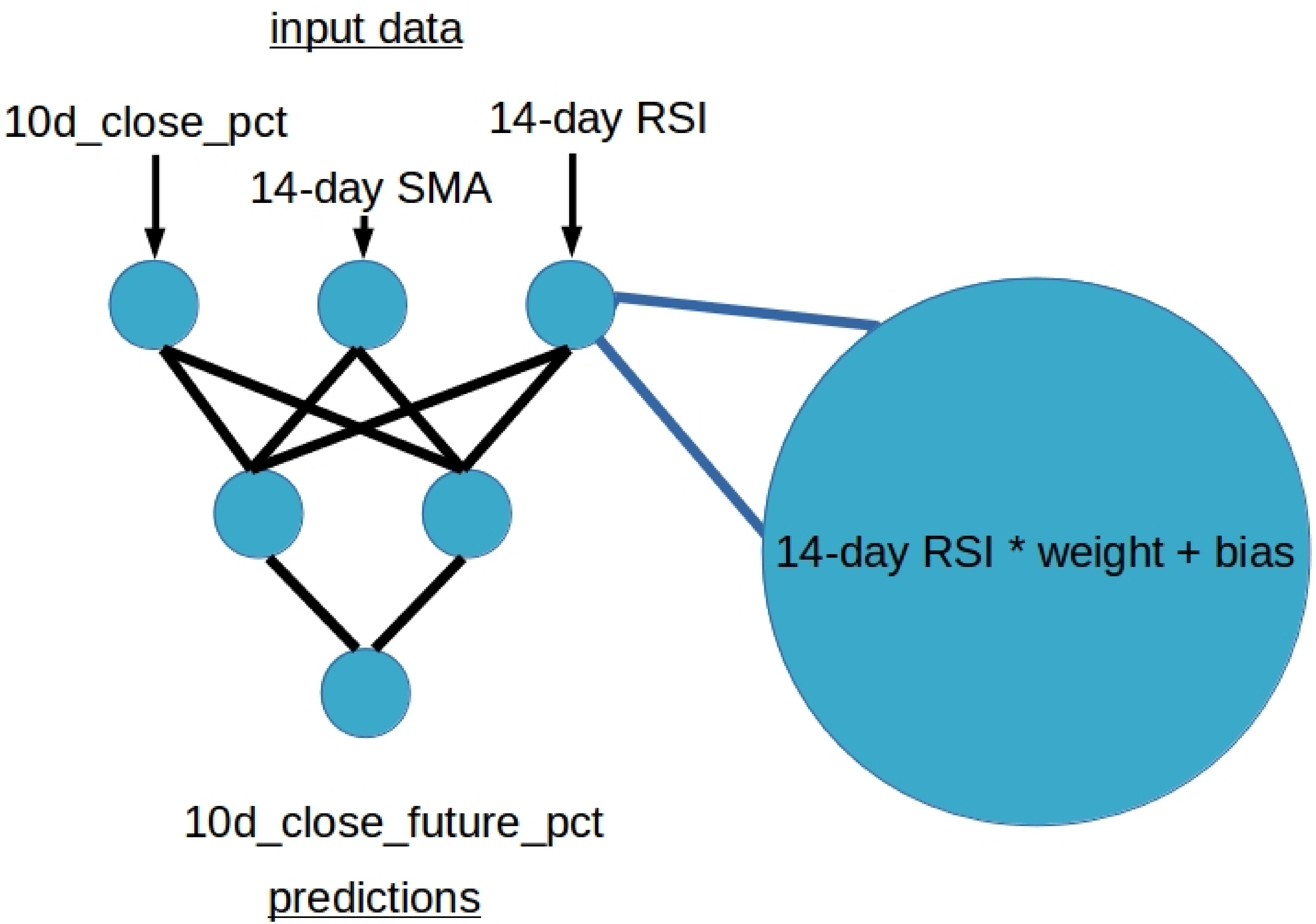

GPU computational power over time
GPU transistor count
10^{10}
10^9
10^8
10^7
2000
2005
2010
2015
Year

Neural networks have potential

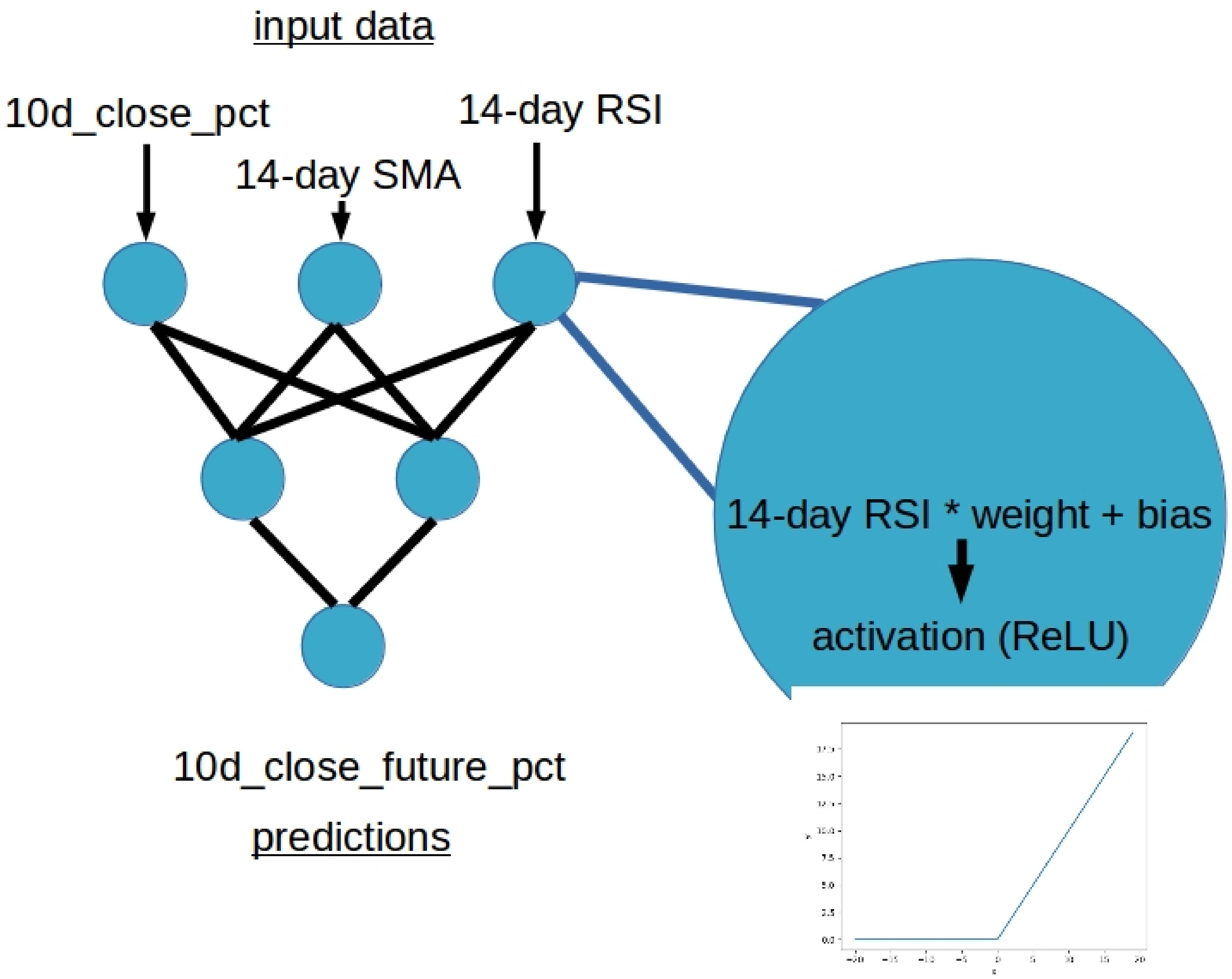
Neural nets have:

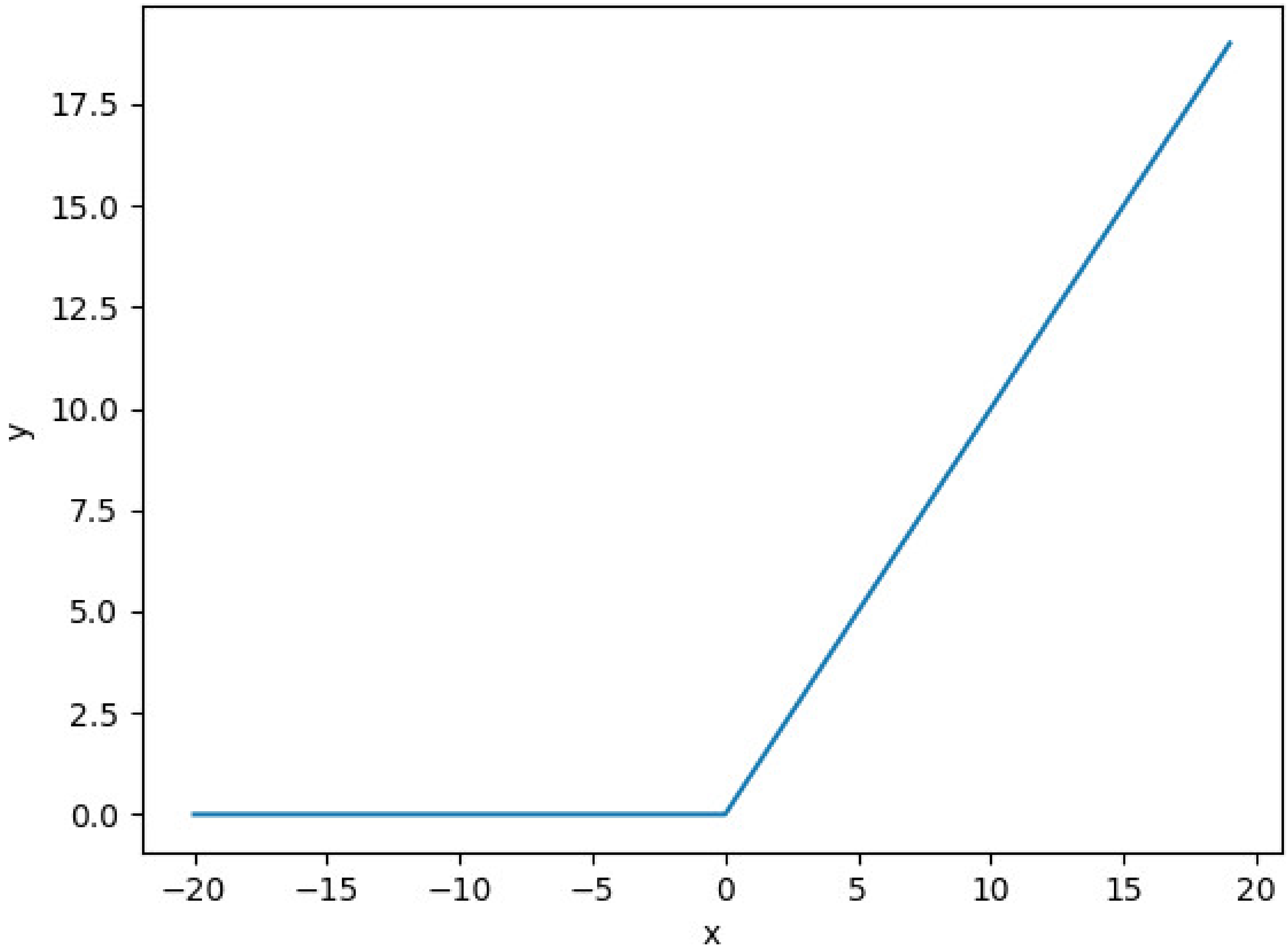
- non-linearity
- variable interactions
- customizability


input data
10d_close_pct
14-day SMA
14-day RSI
10d_close_future_pct
predictions

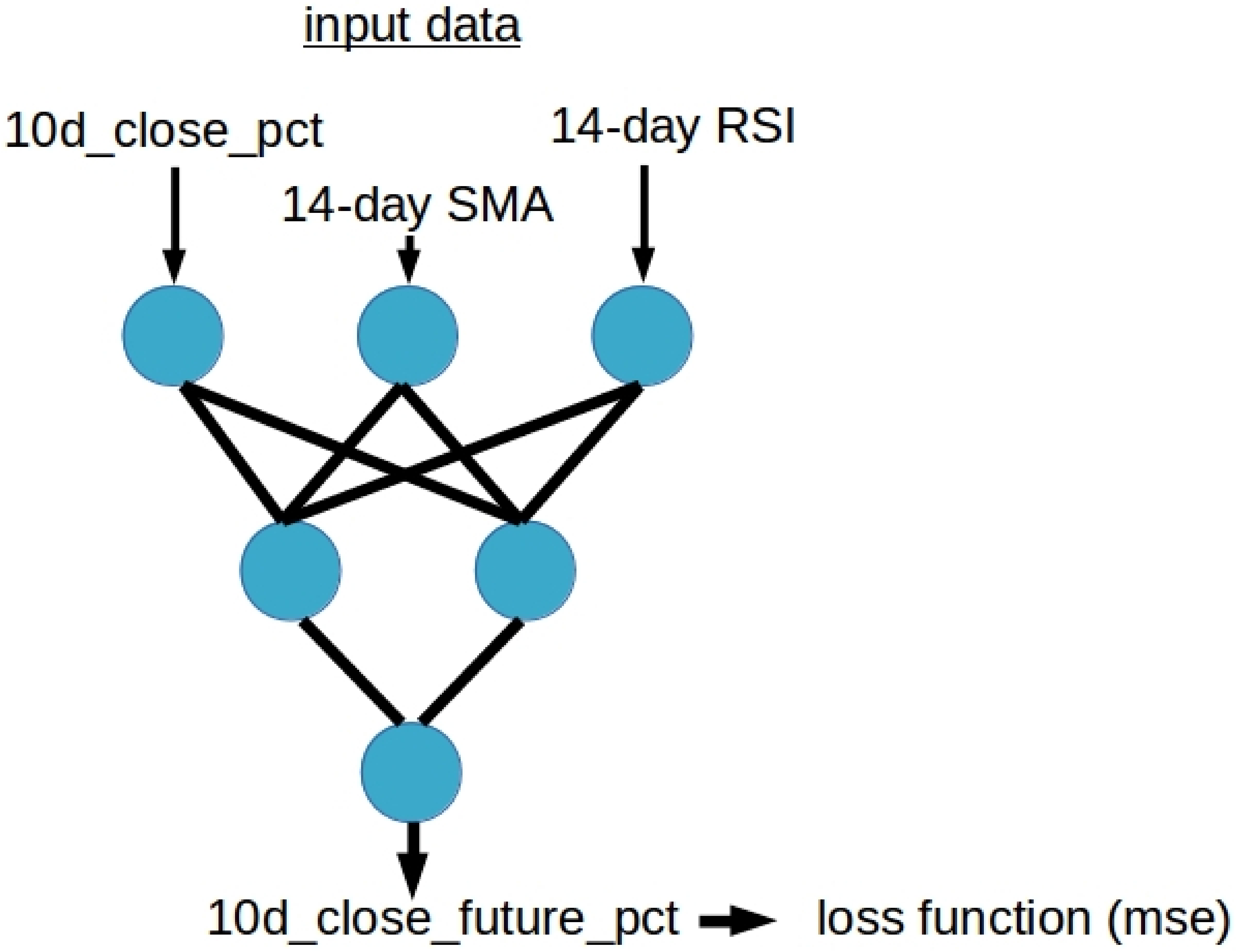

input data
10d_close_pct
14-day SMA
14-day RSI
14-day RSI * weight + bias
10d_close_future_pct
predictions

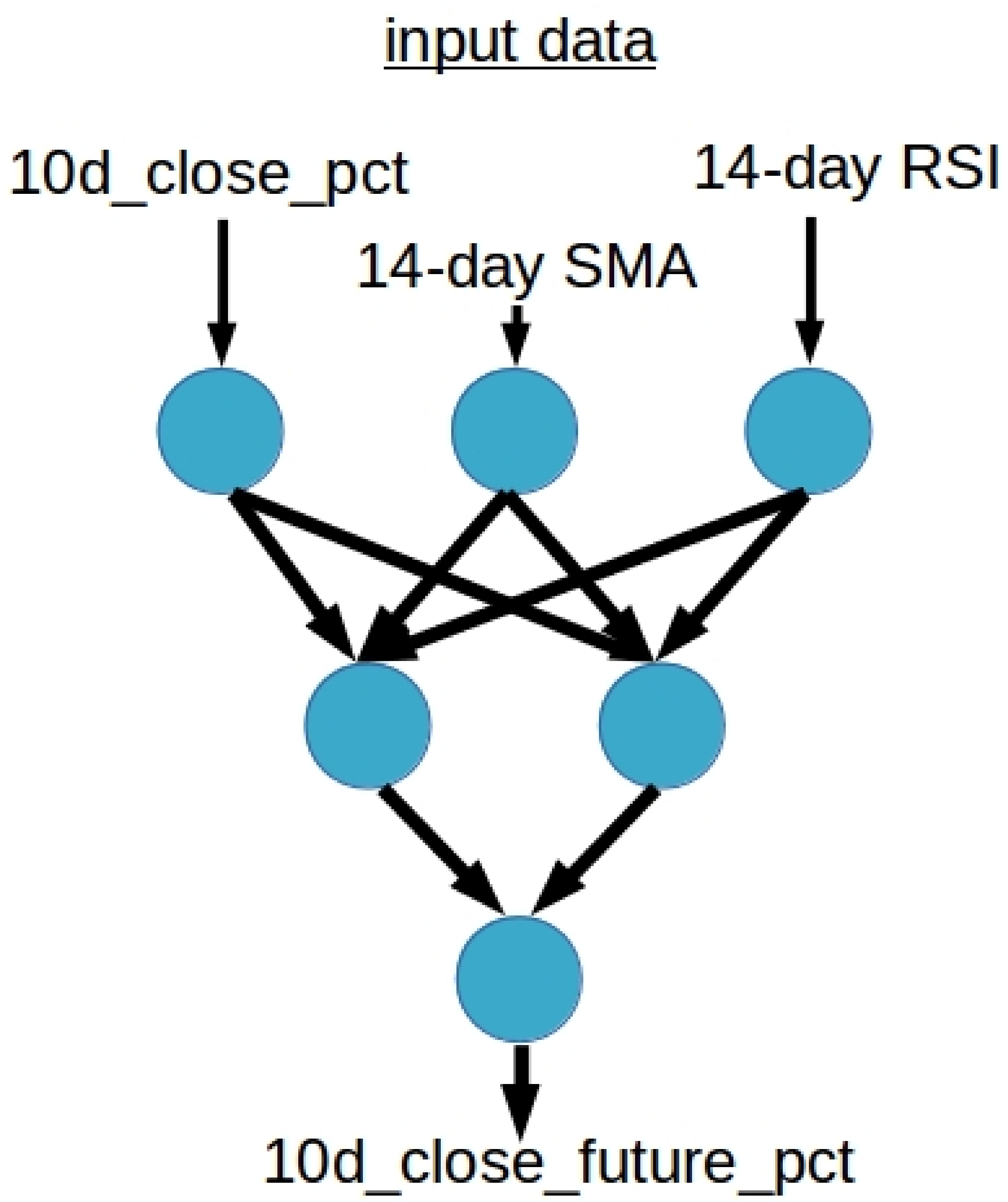
$$\sum_i w_i x_i + b$$

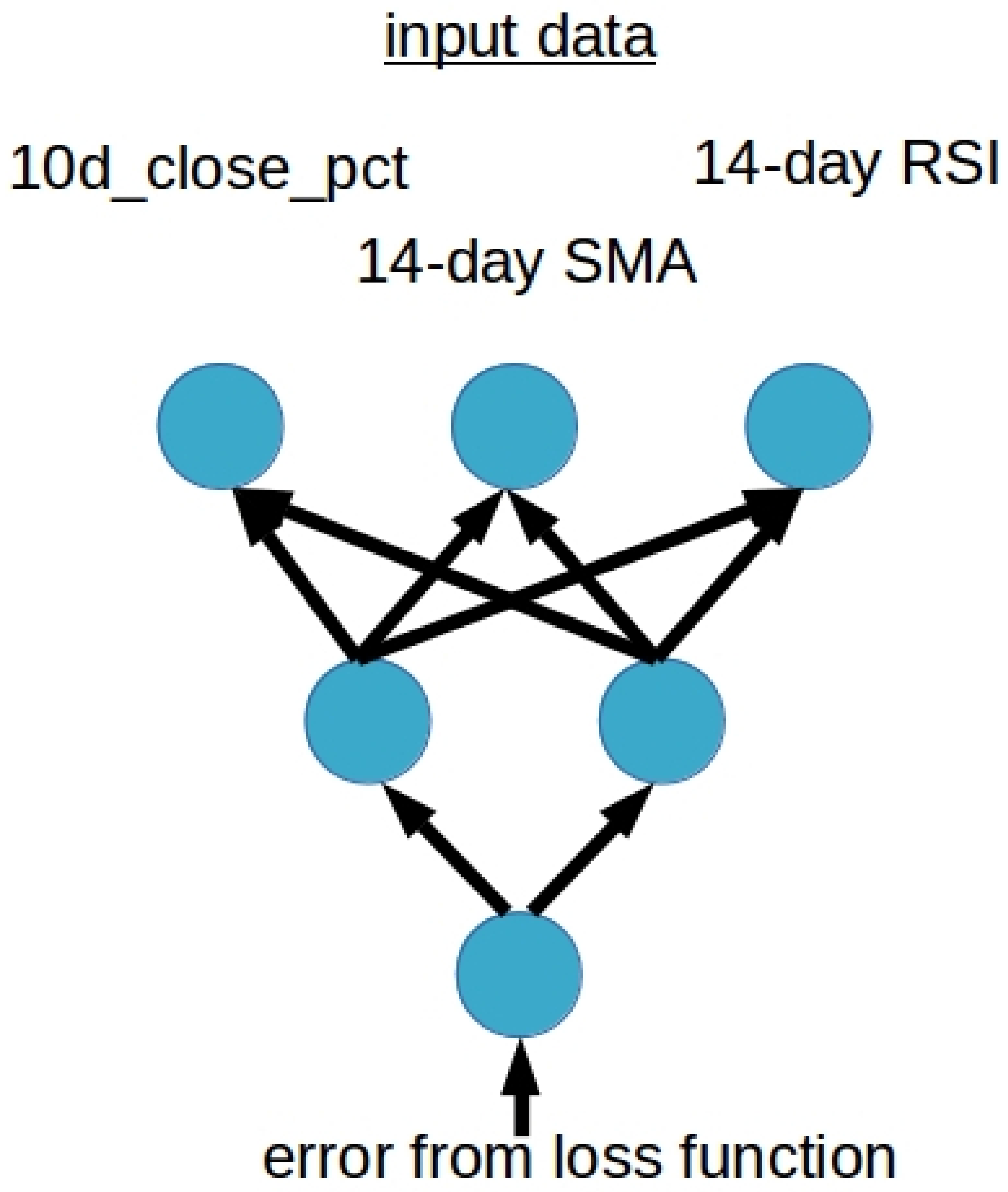

input data
10d_close_pct
14-day SMA
14-day RSI
14-day RSI * weight + bias
activation (ReLU)
10d_close_future_pct
predictions



17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
y
−20
−15
−10
−5
0
5
10
15
20
x


input data
10d_close_pct
14-day SMA
14-day RSI
10d_close_future_pct
loss function (mse)


input data
10d_close_pct
14-day SMA
14-day RSI
10d_close_future_pct


input data
10d_close_pct
14-day RSI
14-day SMA
error from loss function

Keras

Implementing a neural net with keras

```
from keras.models import Sequential
from keras.layers import Dense
```

Implementing a neural net with keras

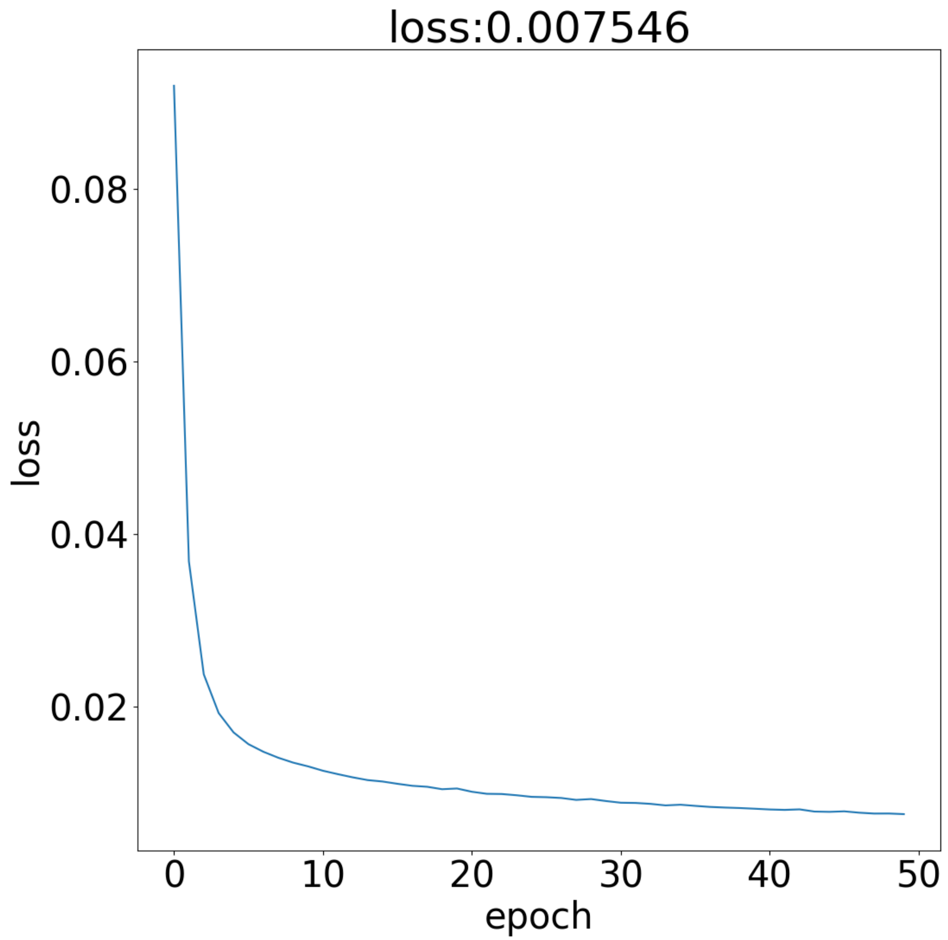
```
from keras.models import Sequential
from keras.layers import Dense

model = Sequential()
model.add(Dense(50,
                input_dim=scaled_train_features.shape[1],
                activation='relu'))
model.add(Dense(10, activation='relu'))
model.add(Dense(1, activation='linear'))
```

Fitting the model

```
model.compile(optimizer='adam', loss='mse')
history = model.fit(scaled_train_features,
                    train_targets,
                    epochs=50)
```

```
plt.plot(history.history['loss'])
plt.title('loss:' + str(round(history.history['loss'][-1], 6)))
plt.xlabel('epoch')
plt.ylabel('loss')
plt.show()
```



Checking out performance

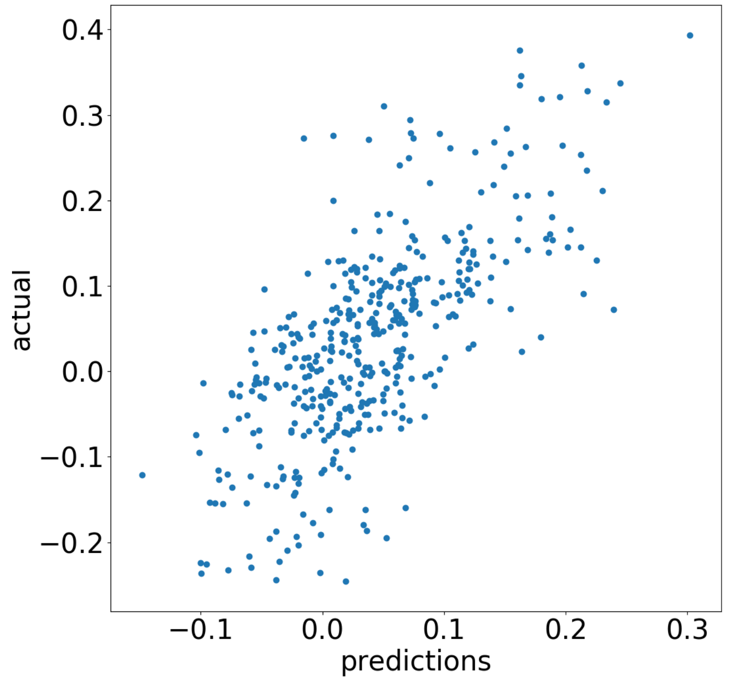
```python
from sklearn.metrics import r2_score

# calculate R^2 score
train_preds = model.predict(scaled_train_features)
print(r2_score(train_targets, train_preds))
```

```
0.4771387560719418
```

Plot performance

```
# plot predictions vs actual
plt.scatter(train_preds, train_targets)
plt.xlabel('predictions')
plt.ylabel('actual')
plt.show()
```



Make a neural net!

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Custom loss functions

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Nathan George
Data Science Professor

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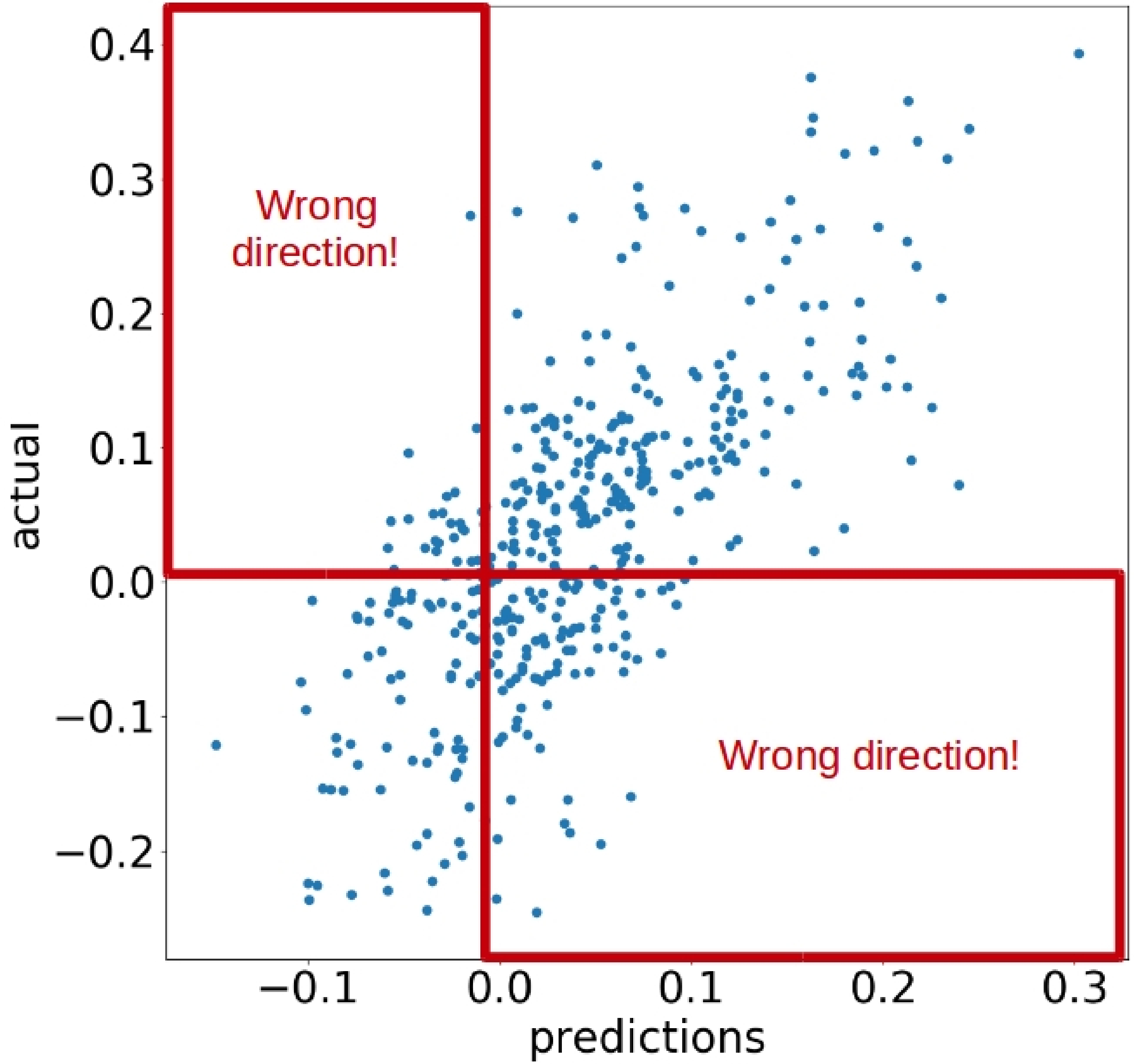

0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
actual
Wrong
direction!
Wrong direction!
−0.1
0.0
0.1
0.2
0.3
predictions

MSE with directional penalty

If prediction and target direction match:

- $\sum(y - \hat{y})^2$

If not:

- $\sum(y - \hat{y})^2 * \text{penalty}$

Implementing custom loss functions

```
import tensorflow as tf
```

Creating a function

```python
import tensorflow as tf
# create loss function
def mean_squared_error(y_true, y_pred):
```

Mean squared error loss

```
import tensorflow as tf


# create loss function
def mean_squared_error(y_true, y_pred):
    loss = tf.square(y_true - y_pred)
    return tf.reduce_mean(loss, axis=-1)
```

Add custom loss to keras

```
import tensorflow as tf

# create loss function
def mean_squared_error(y_true, y_pred):
    loss = tf.square(y_true - y_pred)
    return tf.reduce_mean(loss, axis=-1)
# enable use of loss with keras
import keras.losses
keras.losses.mean_squared_error = mean_squared_error
```

```
# fit the model with our mse loss function
model.compile(optimizer='adam', loss=mean_squared_error)
history = model.fit(scaled_train_features, train_targets, epochs=50)
```

Checking for correct direction

```
tf.less(y_true * y_pred, 0)
```

Correct direction:

- neg * neg = pos
- pos * pos = pos

Wrong direction:

- neg * pos = neg
- pos * neg = neg

Using tf.where()

```
# create loss function
def sign_penalty(y_true, y_pred):
    penalty = 10.
    loss = tf.where(tf.less(y_true * y_pred, 0),
                    penalty * tf.square(y_true - y_pred),
                    tf.square(y_true - y_pred))
```

Tying it together

```
# create loss function
def sign_penalty(y_true, y_pred):
    penalty = 100.
    loss = tf.where(tf.less(y_true * y_pred, 0),
                    penalty * tf.square(y_true - y_pred),
                    tf.square(y_true - y_pred))

    return tf.reduce_mean(loss, axis=-1)
# enable use of loss with keras
keras.losses.sign_penalty = sign_penalty
```

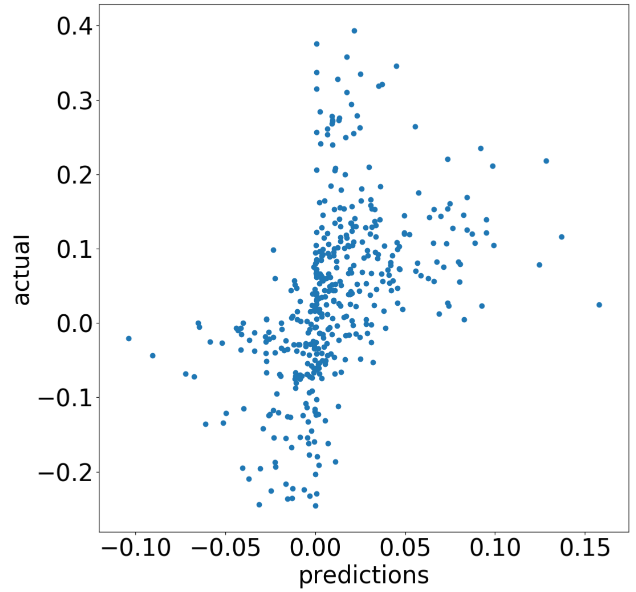
Using the custom loss

```
# create the model
model = Sequential()
model.add(Dense(50,
                input_dim=scaled_train_features.shape[1],
                activation='relu'))
model.add(Dense(10, activation='relu'))
model.add(Dense(1, activation='linear'))
```

```
# fit the model with our custom 'sign_penalty' loss function
model.compile(optimizer='adam', loss=sign_penalty)
history = model.fit(scaled_train_features, train_targets, epochs=50)
```

The bow-tie shape

```
train_preds = model.predict(scaled_train_features)
# scatter the predictions vs actual
plt.scatter(train_preds, train_targets)
plt.xlabel('predictions')
plt.ylabel('actual')
plt.show()
```



Create your own loss function!

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Overfitting and ensembling

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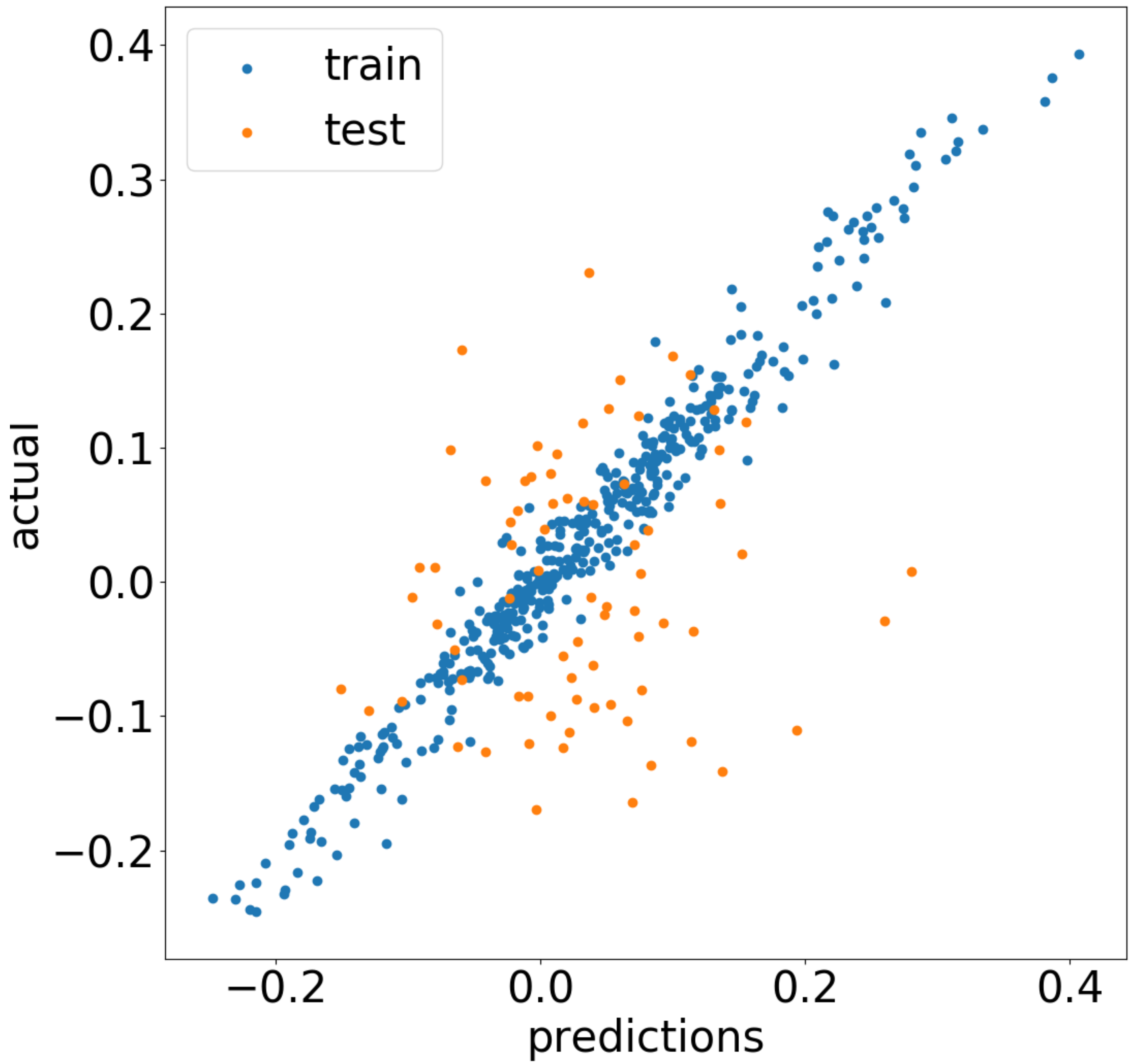
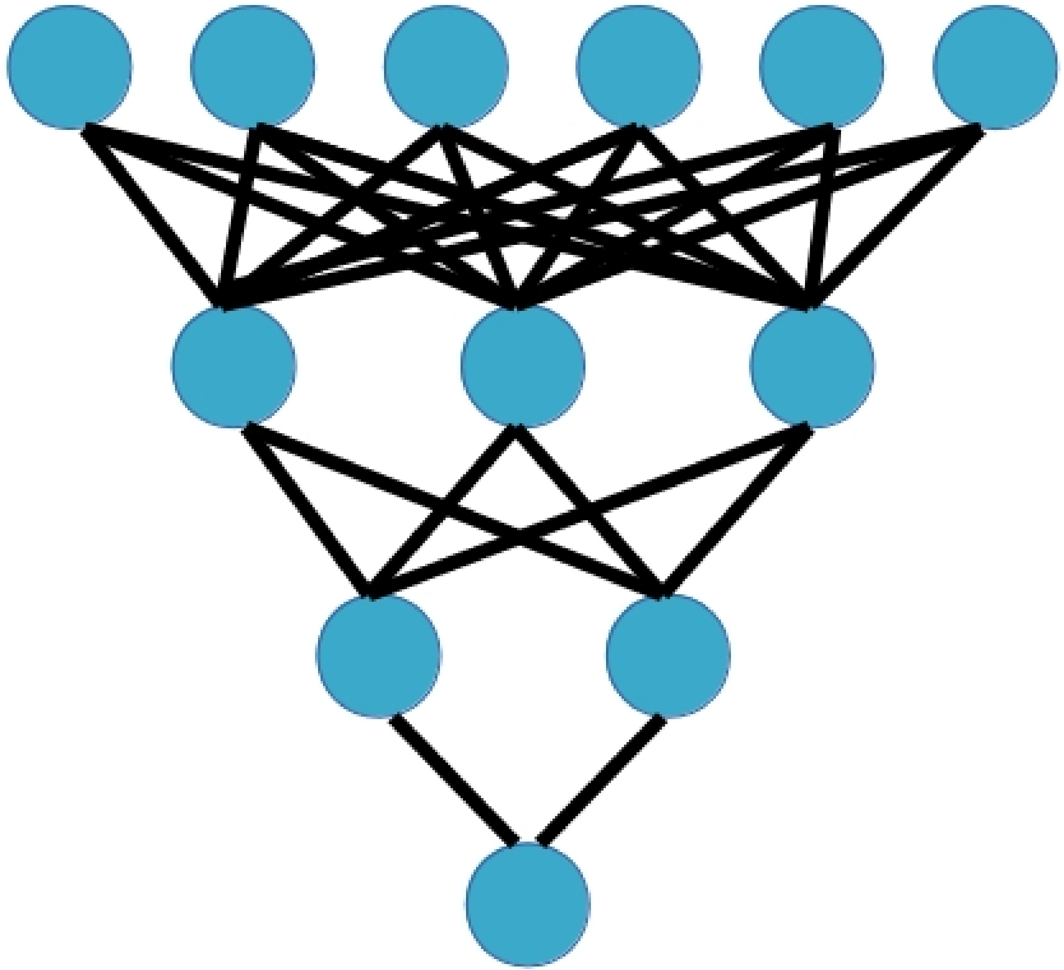
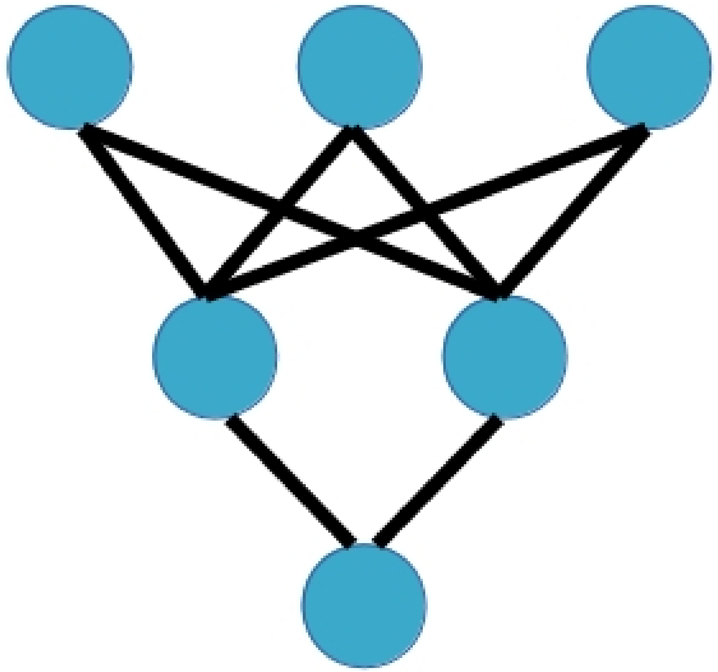

train
test
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
actual
−0.2
0.0
0.2
0.4
predictions

Simplify your model

Complex net overfits



Simpler net prevents overfitting

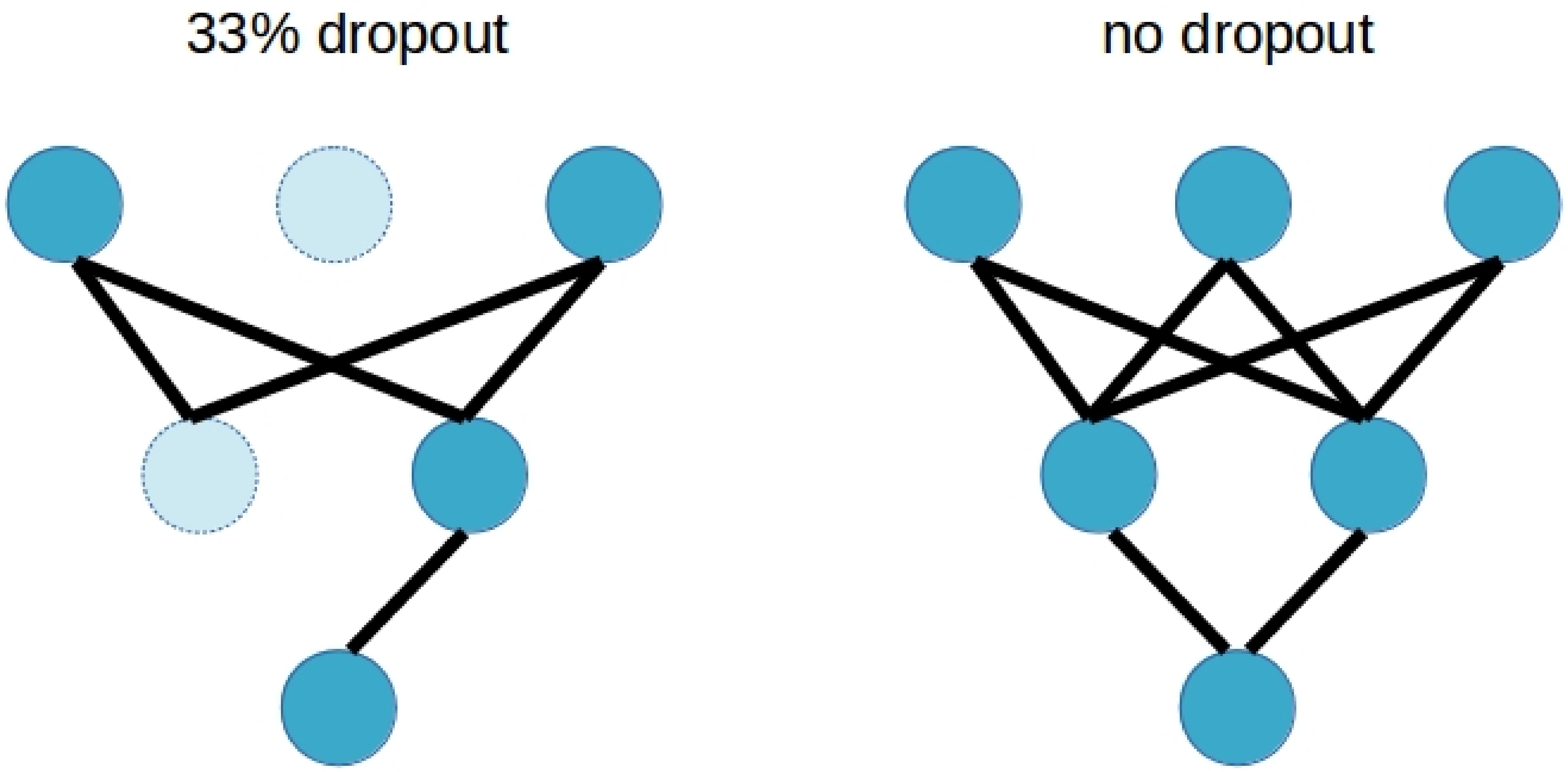


Neural network options

Options to combat overfitting:

- Decrease number of nodes
- Use L1/L2 regulariation
- Dropout
- Autoencoder architecture
- Early stopping
- Adding noise to data
- Max norm constraints
- Ensembling

Dropout



Dropout in keras

```
from keras.layers import Dense, Dropout
model = Sequential()
model.add(Dense(500,
                input_dim=scaled_train_features.shape[1],
                activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(100, activation='relu'))
model.add(Dense(1, activation='linear'))
```

Test set comparison

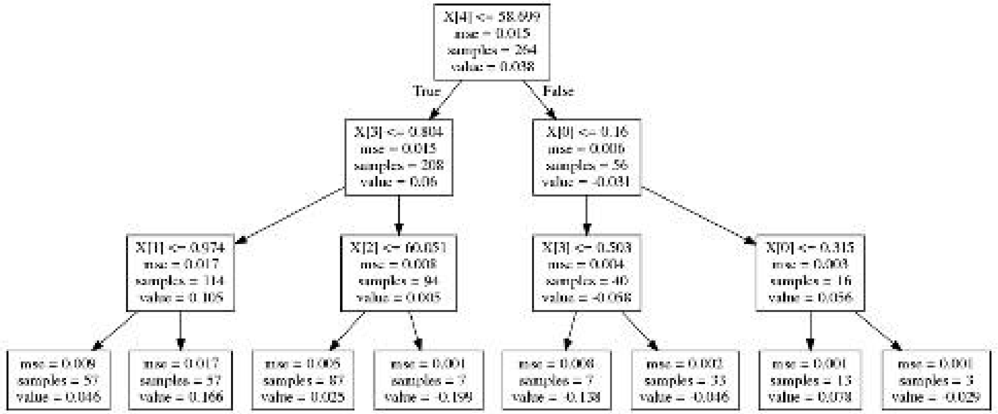
R^2 values on AMD without dropout:

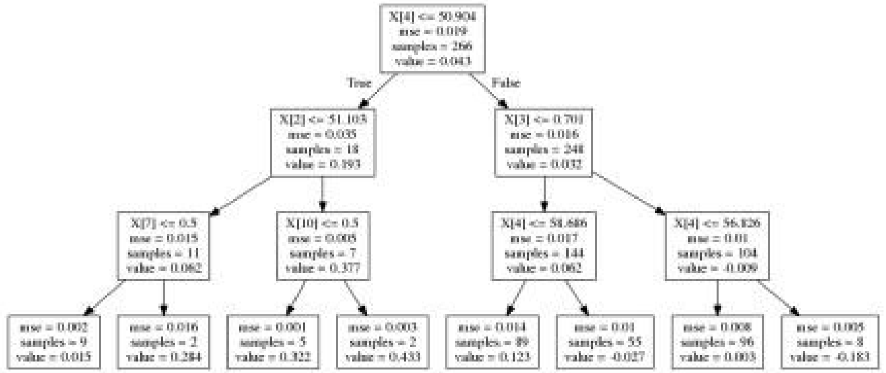
- train: 0.91
- test: -0.72

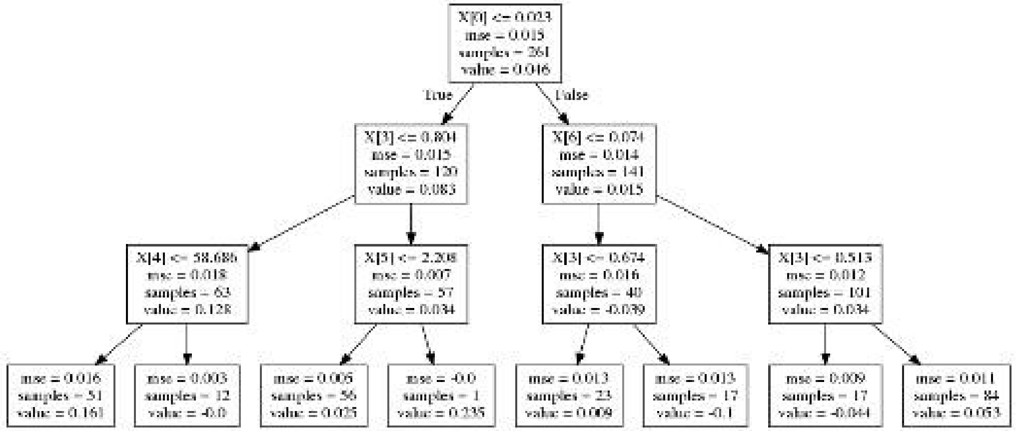
With dropout:

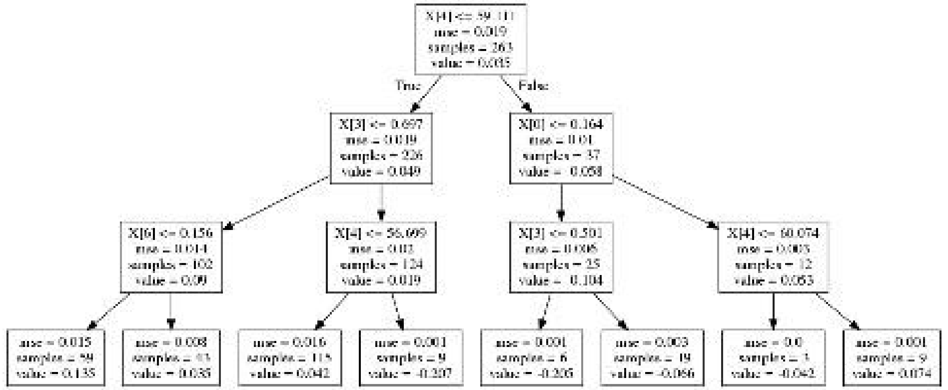
- train: 0.46
- test: -0.22

Ensembling









Implementing ensembling

```
# make predictions from 2 neural net models
test_pred1 = model_1.predict(scaled_test_features)
test_pred2 = model_2.predict(scaled_test_features)
# horizontally stack predictions and take the average across rows
test_preds = np.mean(np.hstack((test_pred1, test_pred2)), axis=1)
```

Comparing the ensemble

Model 1 R^2 score on test set:

- -0.179

model 2:

- -0.148

ensemble (averaged predictions):

- -0.146

Dropout and ensemble!

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