Introduction to explainable AI

EXPLAINABLE AI IN PYTHON

Fouad Trad
Machine Learning Engineer

datacamp

About me

Fouad Trad

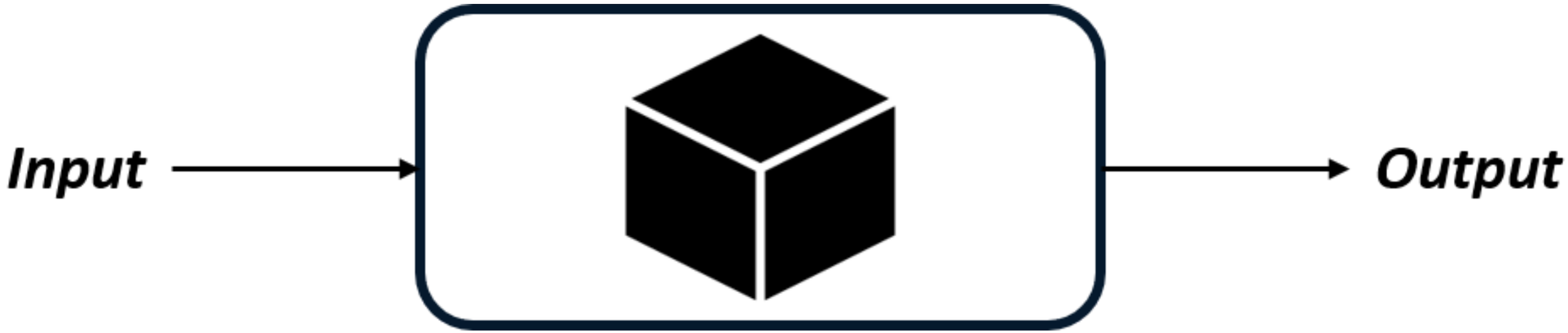
- Machine learning engineer
- PhD Candidate
- Specializing in AI for Cybersecurity

LinkedIn

Artificial intelligence

- AI enables machines to perform human-like tasks

The need for explainability



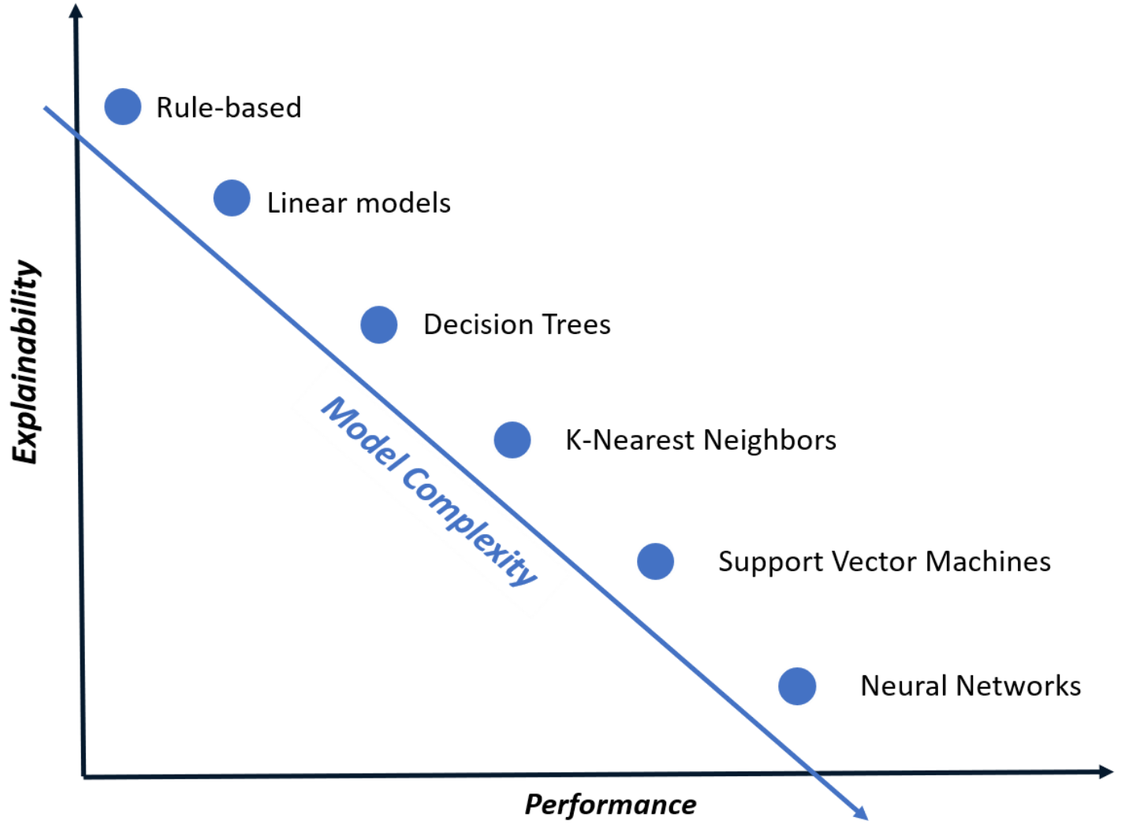
- **Black box AI:** no understanding of decision-making

The need for explainability

- **Black box AI:** no understanding of decision-making
- **Explainable AI:** understand model's inner workings

Explainability vs. accuracy

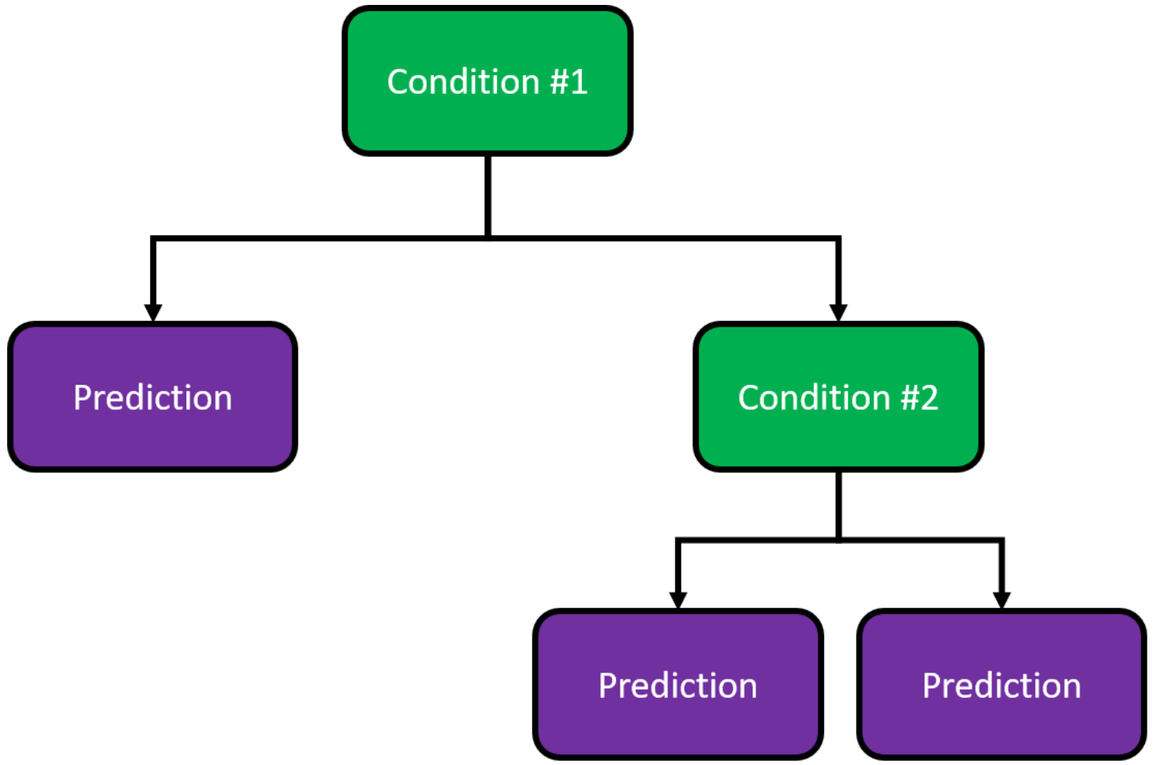
- Basic models are:
  - More explainable
  - Less precise
- Complex models are:
  - More precise
  - Less explainable



Decision trees vs. neural networks

Decision trees

Show decision path based on conditions



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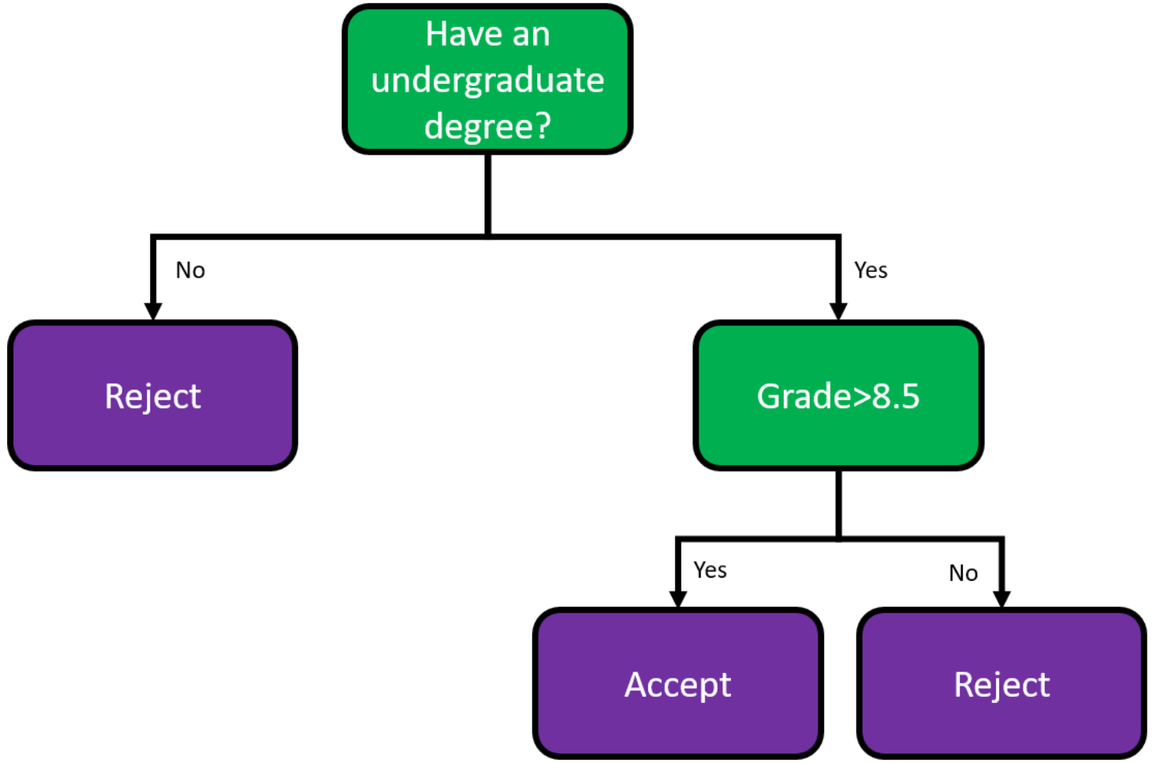

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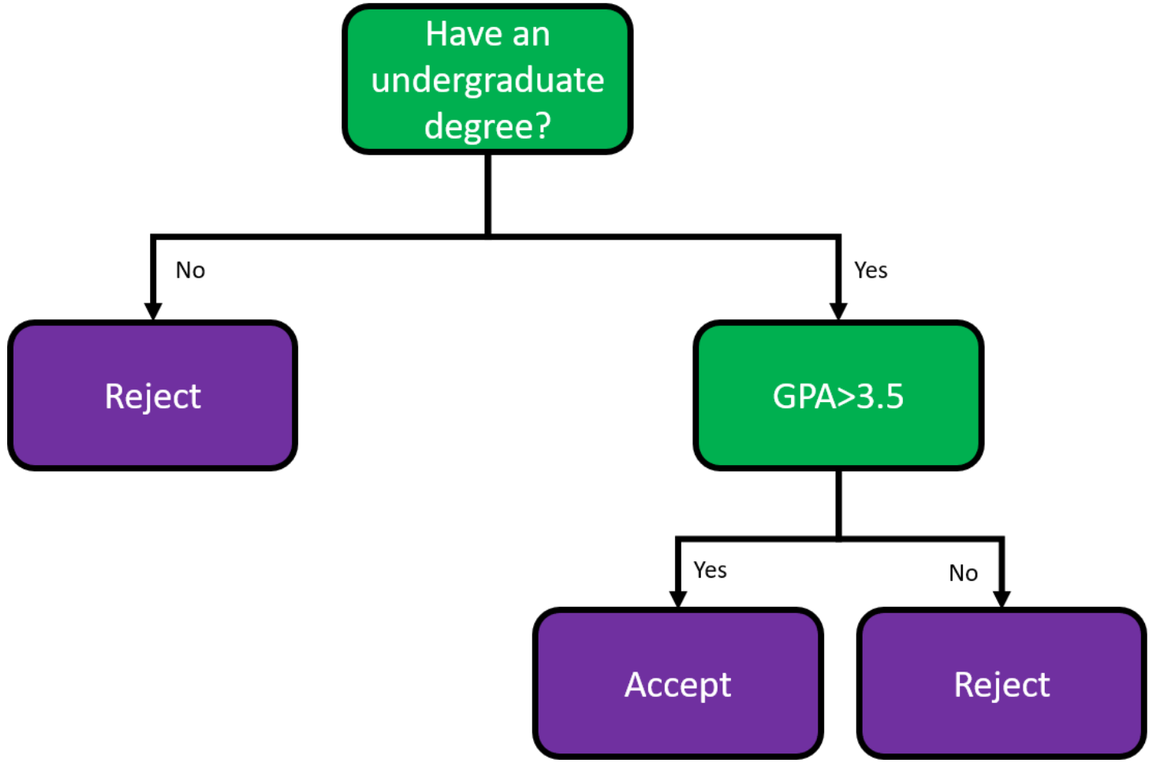
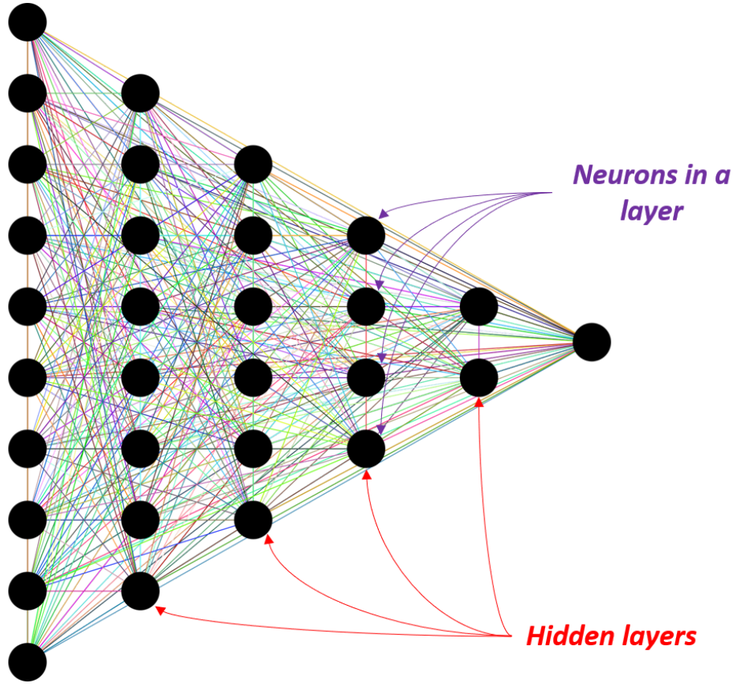


Neural networks

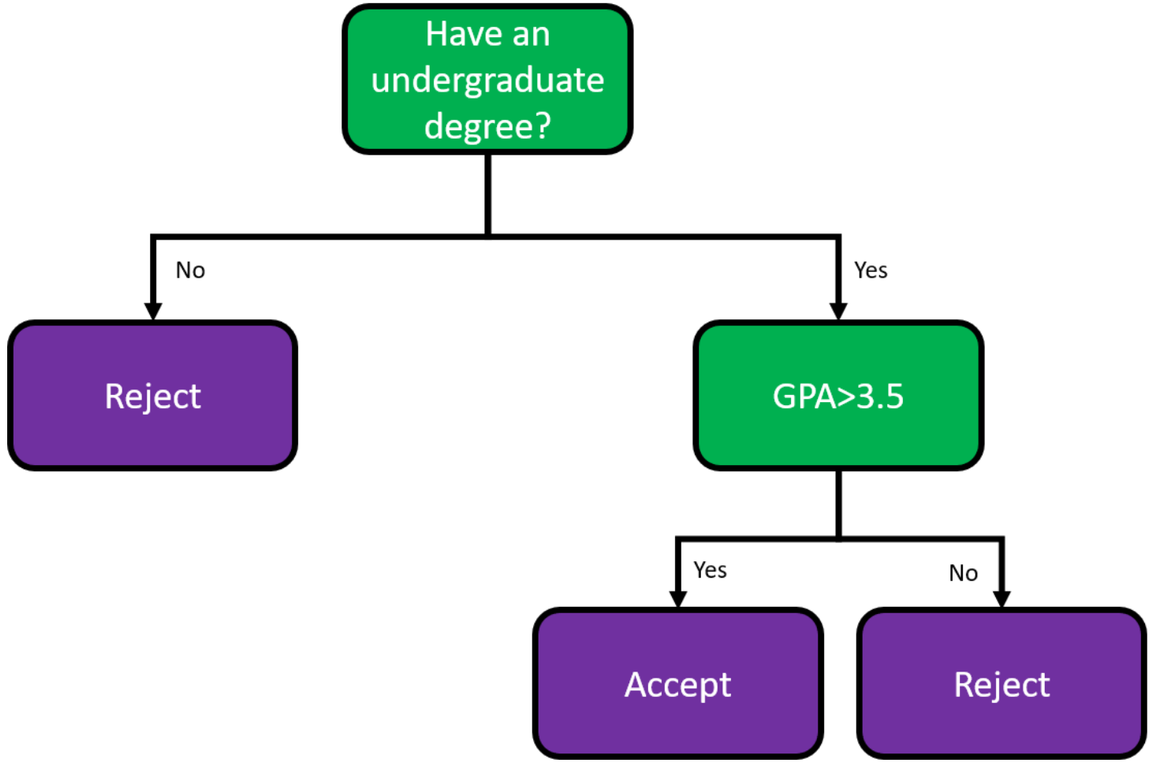
Not inherently transparent



Decision trees vs. neural networks

Decision trees

Show decision path based on conditions



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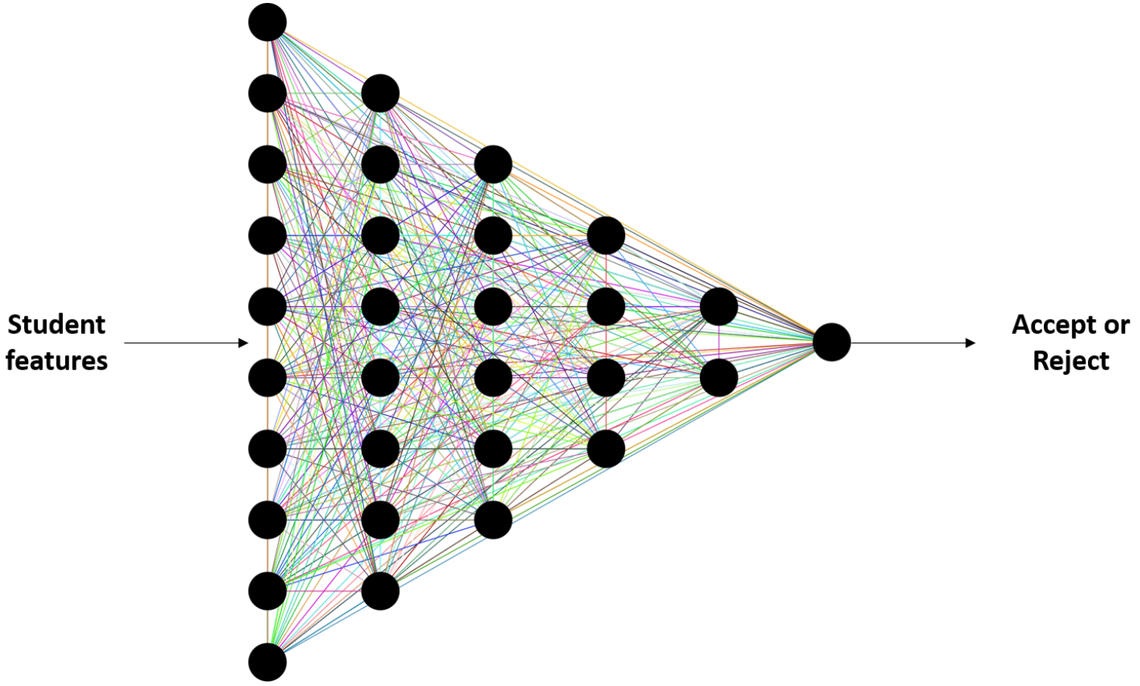

Student admission prediction

GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Accept
337	118	4	4.5	4.5	9.65	1
316	104	3	3	3.5	8.00	1
314	103	2	2	3	8.21	0

- Test scores: GRE and TOEFL
- University rating
- SOP: statement of purpose
- LOR: letter of recommendation
- CGPA: cumulative grade point average

Student admission prediction

Decision Tree

```
from sklearn.tree import DecisionTreeClassifier

model = DecisionTreeClassifier(max_depth=5)

model.fit(X_train, y_train)

y_pred = model.predict(y_test)

acc = accuracy_score(y_test, y_pred)
print(f"Accuracy of Decision Tree: {acc}")
```

```
Accuracy of Decision Tree: 0.82
```

Neural Network

```
from sklearn.neural_network import MLPClassifier

model = MLPClassifier(hidden_layer_sizes=(1000,1000))

model.fit(X_train, y_train)

y_pred = model.predict(y_test)

acc = accuracy_score(y_test, y_pred)
print(f"Accuracy of Neural Network: {acc}")
```

```
Accuracy of Neural Network: 0.9
```

Decision tree rules

```
from sklearn.tree export_text

rules = export_text(model, feature_names=list(X_train.columns))

print(rules)
```

```
|--- CGPA <= 8.34
|   |--- GRE Score <= 320.50
|   |   |--- class: 0
|   |--- GRE Score >  320.50
|   |   |--- class: 1
|--- CGPA >  8.34
|   |--- GRE Score <= 319.50
|   |   |--- class: 1
...
```

Model-specific vs. model-agnostic techniques

Model-specific

Apply to particular model

Model-specific vs. model-agnostic techniques

Model-specific

Apply to particular model

Model-agnostic

Apply to any model

What's next?

- Model-specific and model-agnostic techniques
- Local and global methods
- Advanced topics:
  - Explainability metrics
  - Unsupervised explainability
  - Generative AI explainability

Let's practice!

EXPLAINABLE AI IN PYTHON

Explainability in linear models

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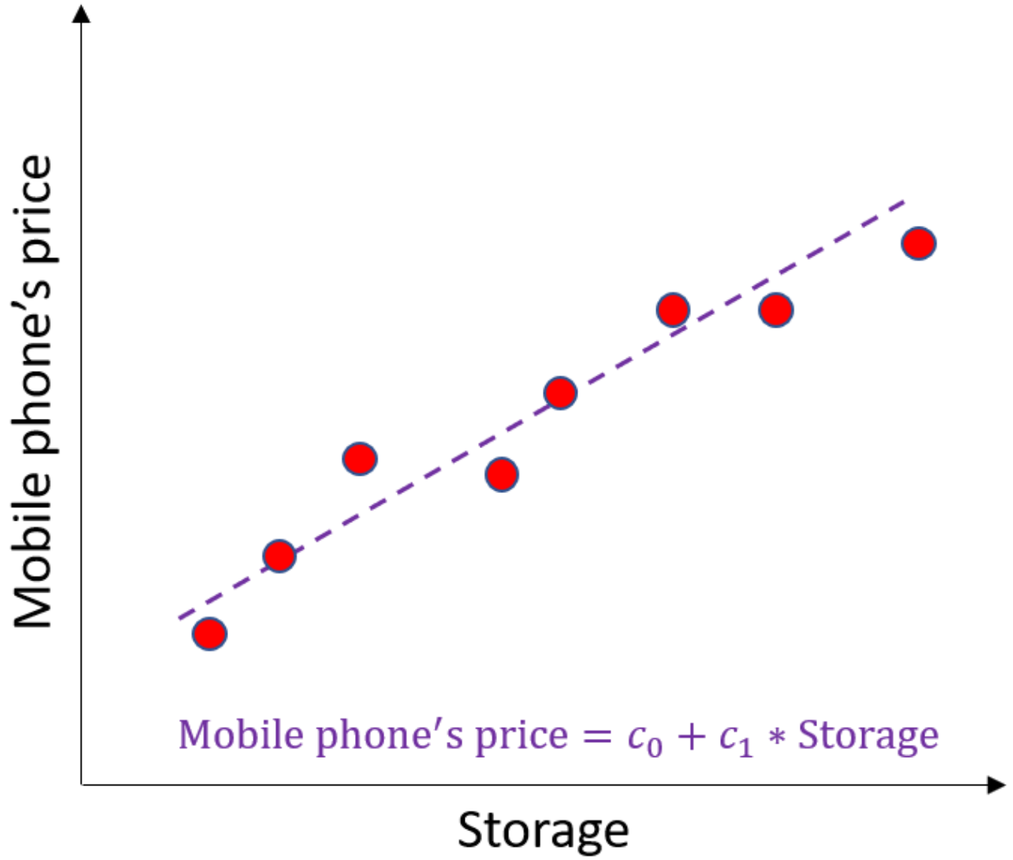
Linear models

Linear regression

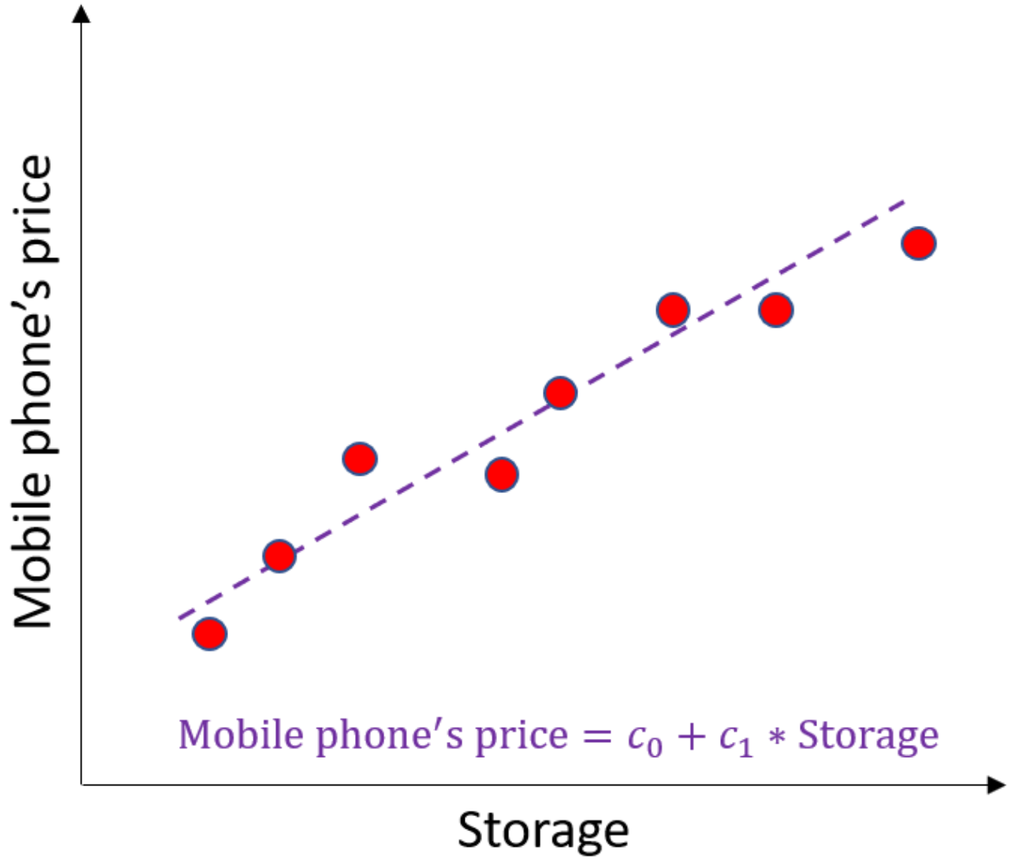
- Predicts continuous values



Linear models

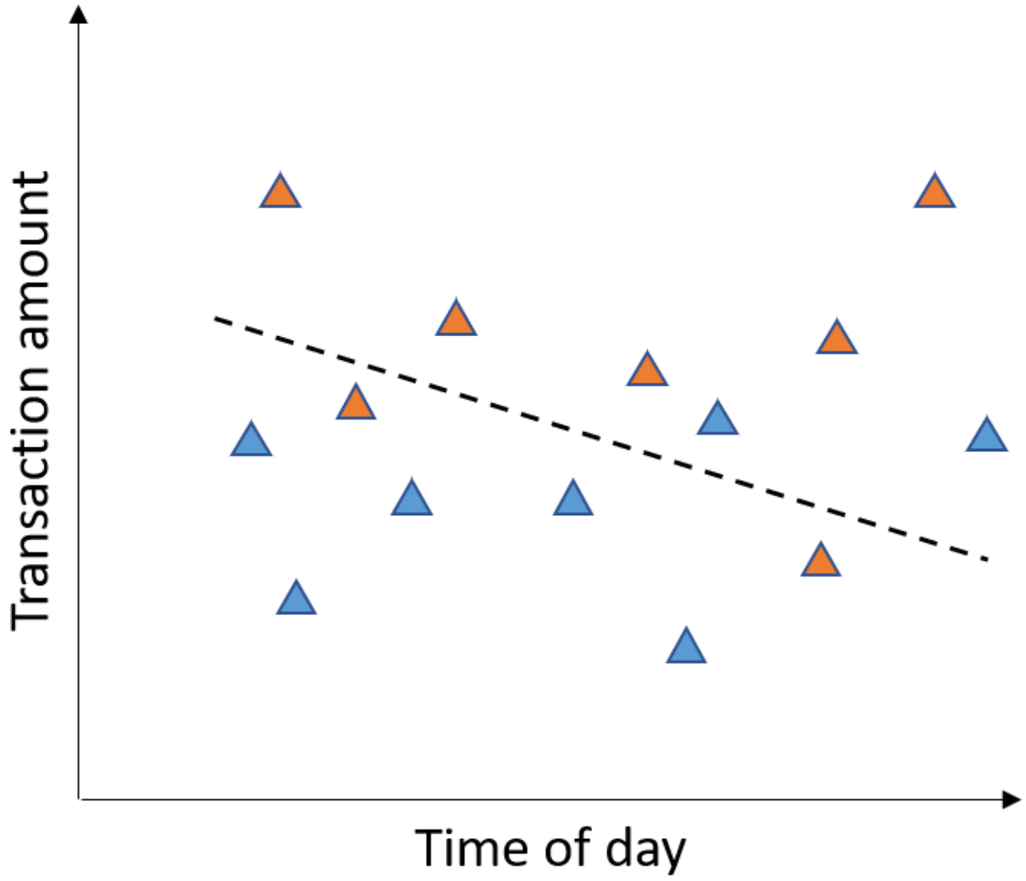
Linear regression

- Predicts continuous values



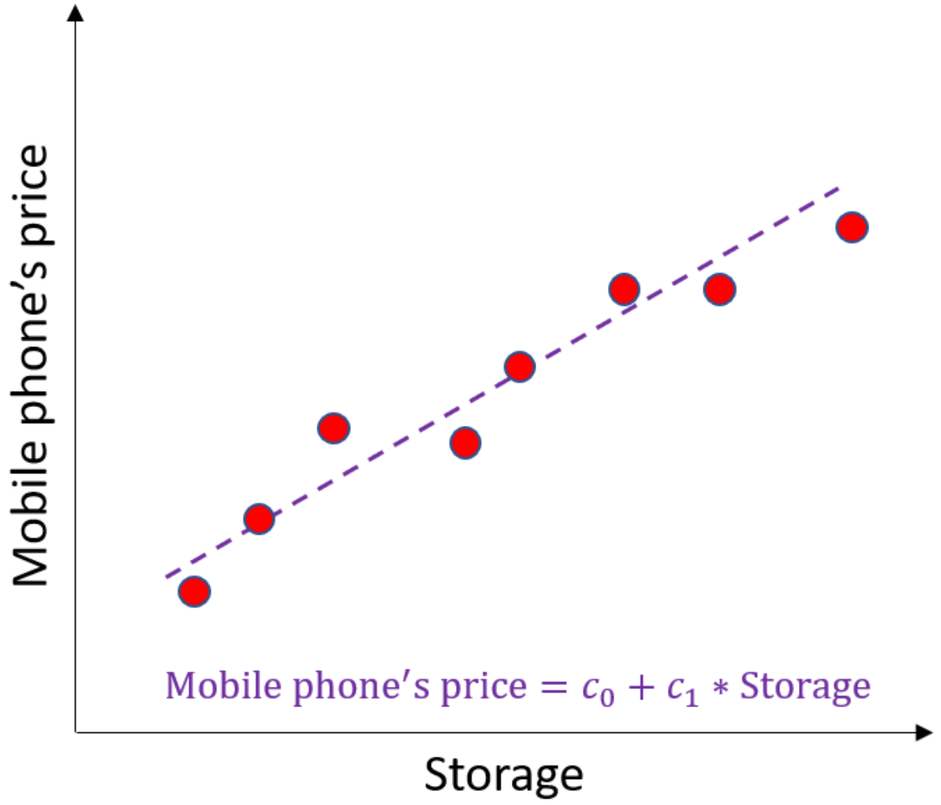
Logistic regression

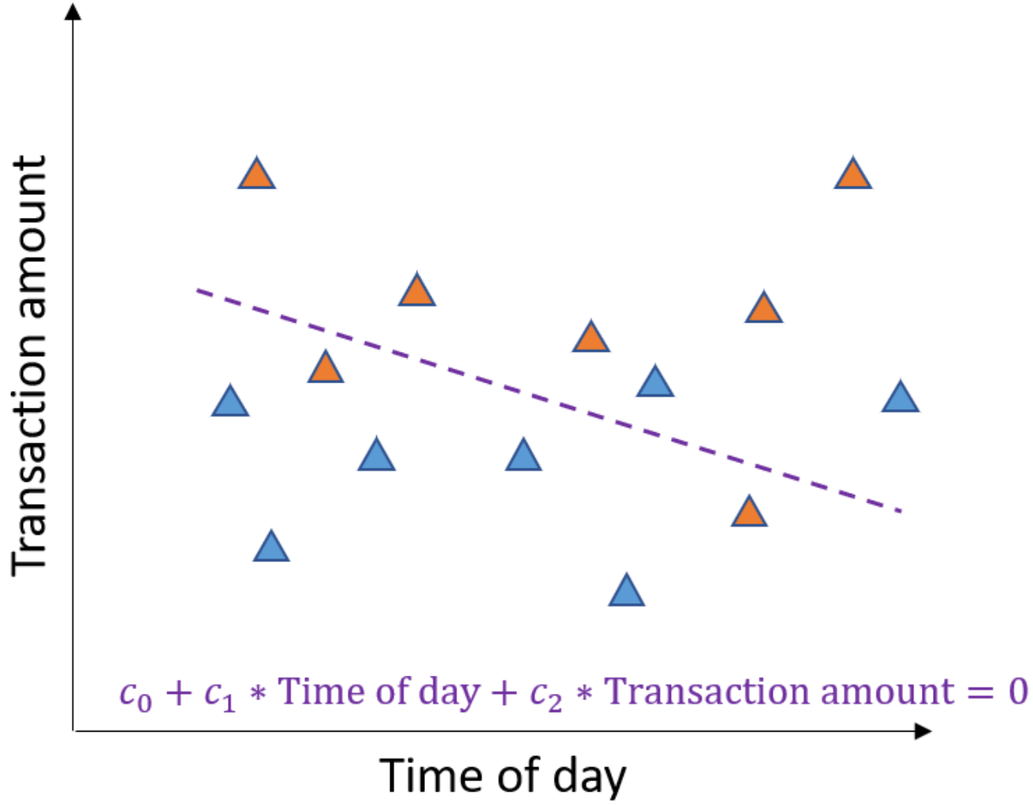
- Used for binary classification



Why are linear models explainable?

- Learn linear combination of input features
- $c_0 + c_1 \times \text{feature}_1 + c_2 \times \text{feature}_2 + \ldots + c_n \times \text{feature}_n$





Coefficients

- Tell us importance of each feature
  - Higher absolute value → higher importance
  - Lower absolute value → lower importance
- To compare coefficients → absolute values
- **Note:** Normalize feature scales before computing coefficients

$$\text{Mobile Phone's price} = c_0 + 5 * Storage + 2 * \text{Number of camera lenses}$$

Coefficients

- Tell us importance of each feature
  - Higher absolute value → higher importance
  - Lower absolute value → lower importance
- To compare coefficients → absolute values
- **Note:** Normalize feature scales before computing coefficients

$$\text{Mobile Phone's price} = c_0 + c_1 * \underbrace{Storage}_{*\,[100\ -1000]GB} + c_2 * \underbrace{\text{Number of camera lenses}}_{<5}$$

Admissions

GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Chance of Admit	Accept
337	118	4	4.5	4.5	9.65	0.92	1
324	107	4	4	4.5	8.87	0.76	1
316	104	3	3	3.5	8	0.72	1
322	110	3	3.5	2.5	8.67	0.8	1
314	103	2	2	3	8.21	0.45	0

```
X_train = data.drop(['Chance of Admit', 'Accept'], axis=1)
y_reg = data['Chance of Admit']
y_cls = data['Accept']
```

Model training

```
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LinearRegression, LogisticRegression

scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)

lin_reg = LinearRegression()
lin_reg.fit(X_train_scaled, y_reg)

log_reg = LogisticRegression()
log_reg.fit(X_train_scaled, y_cls)
```

Computing coefficients

Linear regression

```
print(lin_reg.coef_)
```

```
[0.03052087 0.01665433 0.00668971
 0.00326926 0.01724815 0.0661691 ]
```

Logistic regression

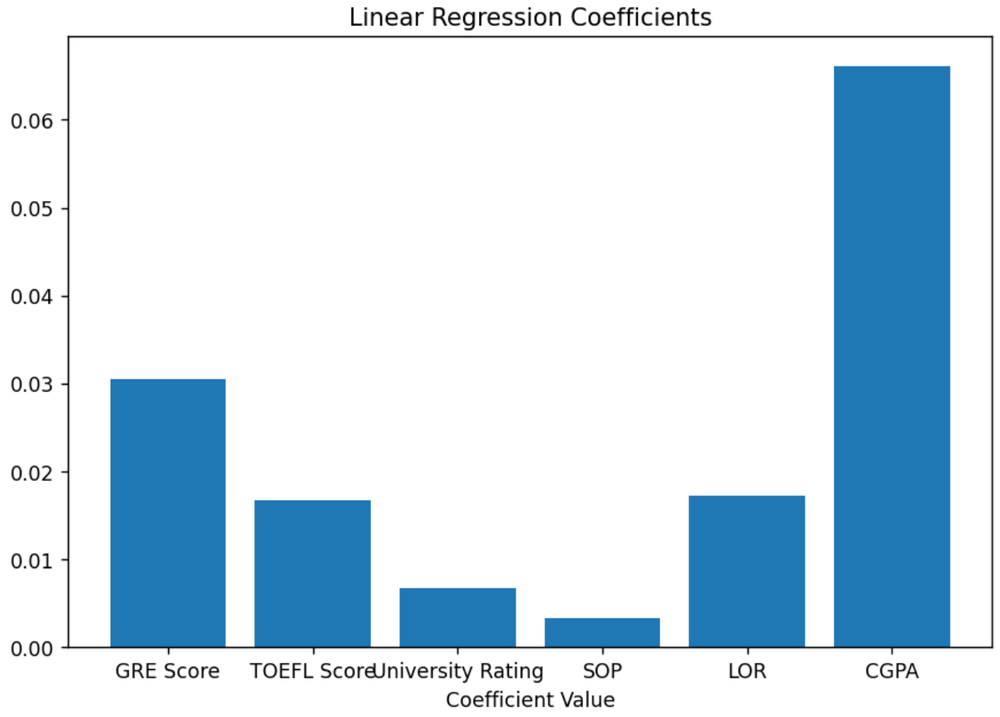
```
print(log_reg.coef_)
```

```
[[1.28985577  0.49441086  0.47593379
  0.05434322  0.41800927  1.31980189]]
```

Visualizing coefficients

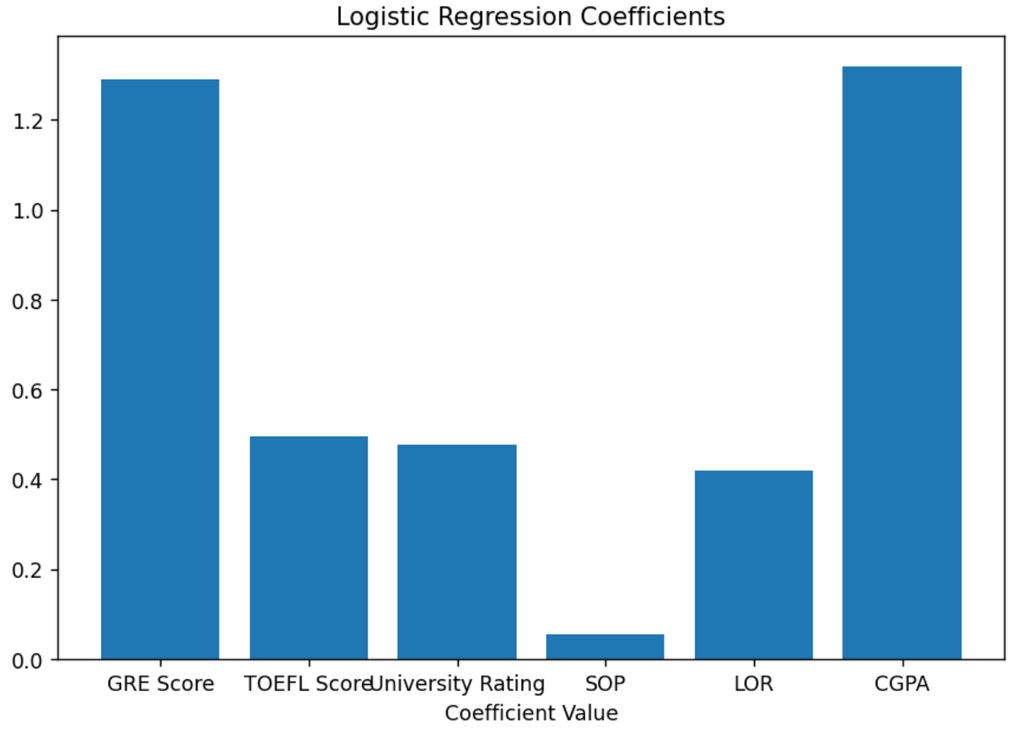
Linear regression

```
import matplotlib.pyplot as plt
plt.bar(X_train.columns, lin_reg.coef_)
```



Logistic regression

```
import matplotlib.pyplot as plt
plt.bar(X_train.columns, log_reg.coef_[0])
```



Let's practice!

EXPLAINABLE AI IN PYTHON

Explainability in tree-based models

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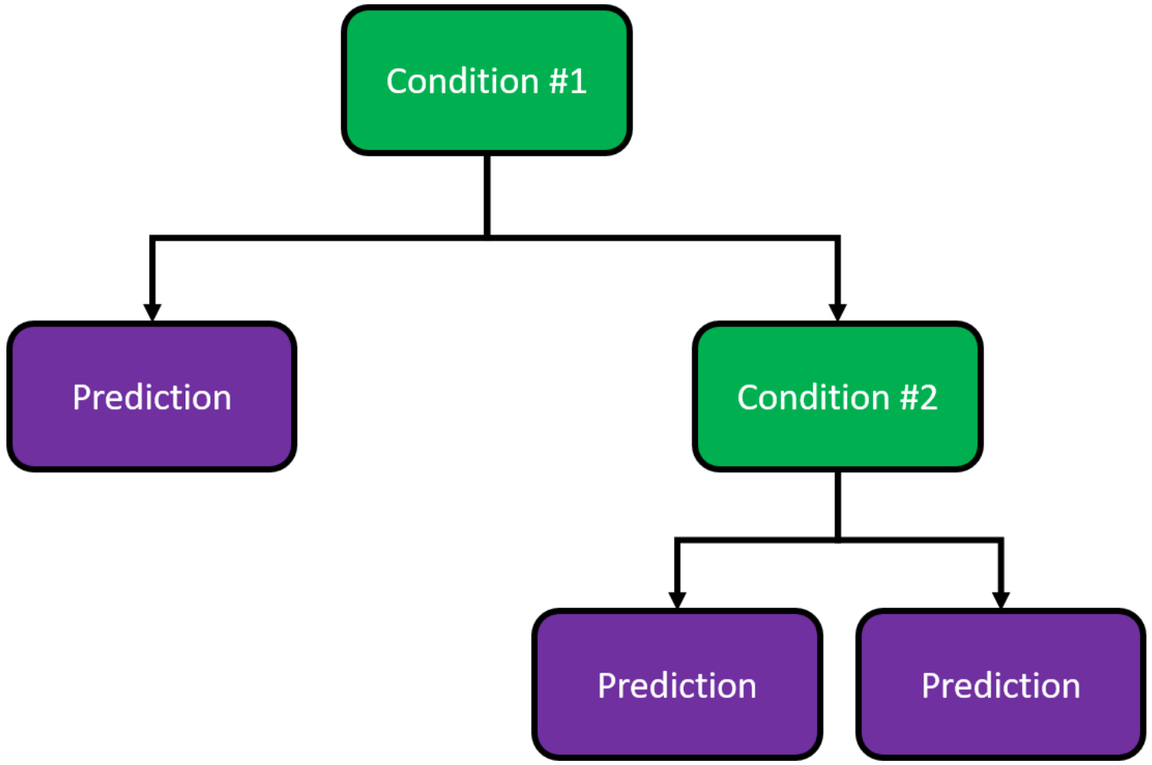
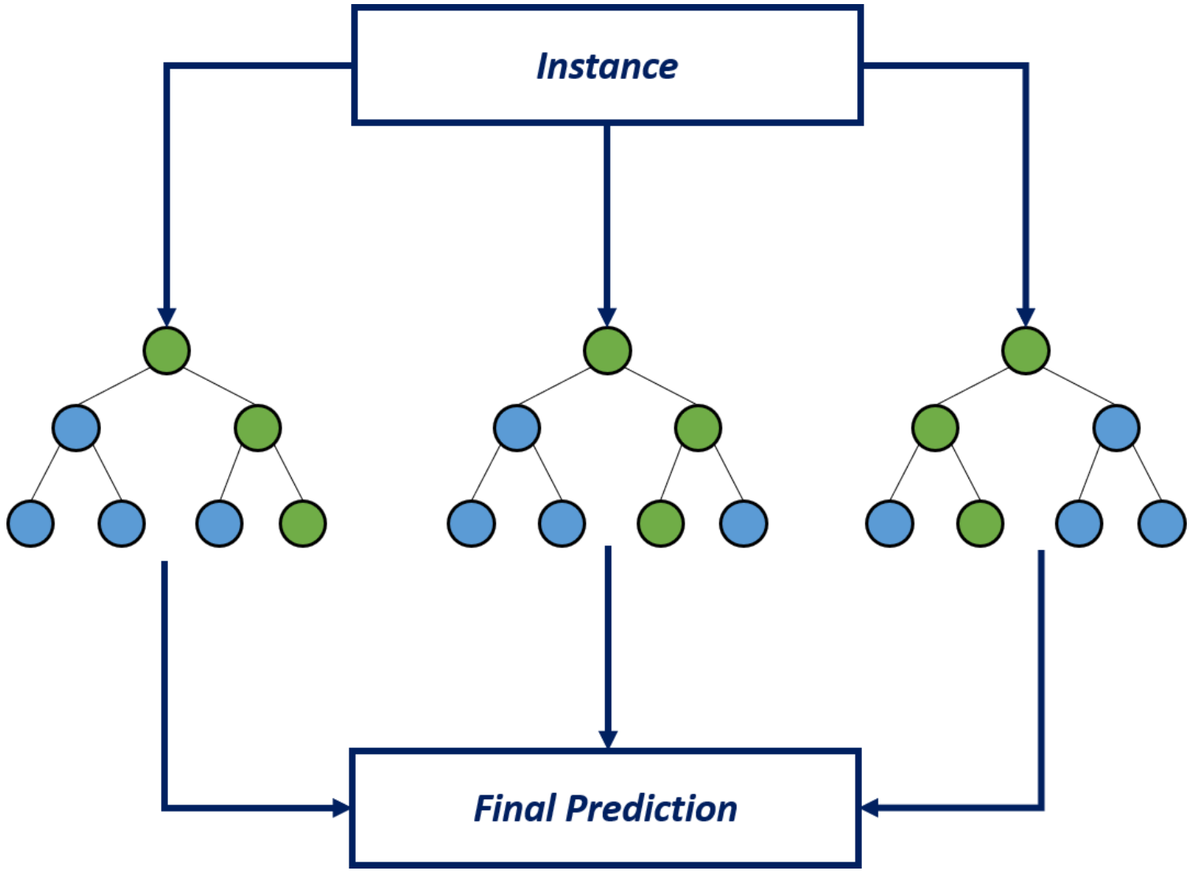
Decision tree

- Fundamental block of tree-based models
- Used for regression and classification
- Tree-like structure for predictions
  - Several decisions
  - Each decision is based on one feature
- Inherently explainable



Random forest

- Consists of many decision trees
- Used for regression and classification
- Complicates direct interpretability
- Feature importance
  - Measures reduction of uncertainty in predictions
  - Different than coefficients in linear models



Admissions dataset

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324	107	4	4	4.5	8.87	1
316	104	3	3	3.5	8.00	1
322	110	3	3.5	2.5	8.67	1
314	103	2	2	3	8.21	0

```
X_train = data.drop(['Accept'], axis=1)
y_train = data['Accept']
```

Model training

```
from sklearn.tree import DecisionTreeClassifier

tree_model = DecisionTreeClassifier()
tree_model.fit(X_train, y_train)

print(tree_model.feature_importances_)
```

```
[0.17936982 0.08878744 0.04388924
 0.0532897  0.07130751 0.56335628]
```

```
from sklearn.ensemble import RandomForestClassifier

forest_model = RandomForestClassifier()
forest_model.fit(X_train, y_train)

print(forest_model.feature_importances_)
```

```
[0.25347149 0.17518662 0.06551317
 0.06758647 0.07866478 0.35957747]
```

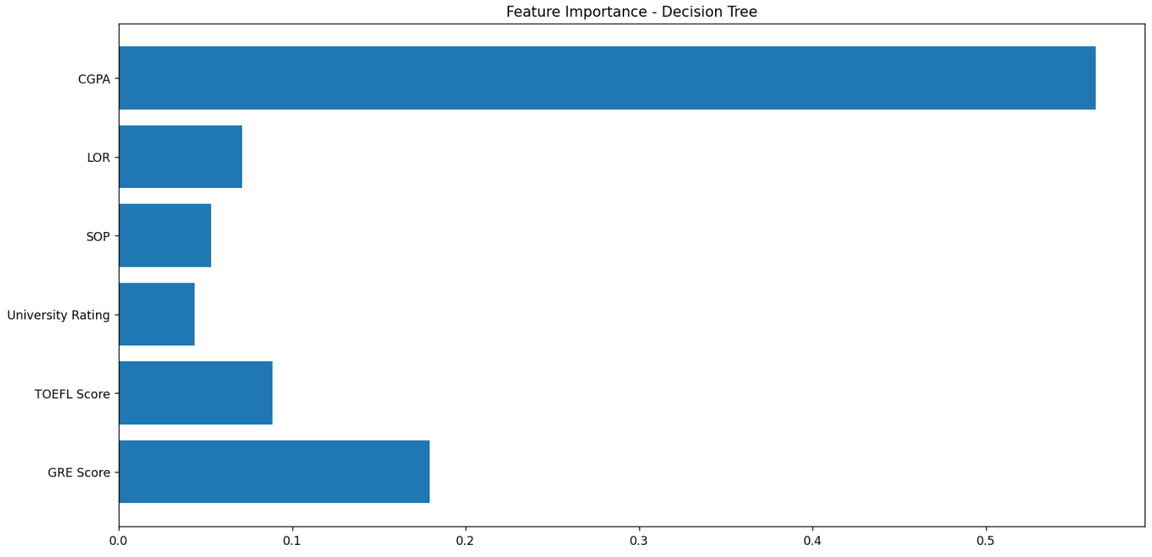
Feature importance

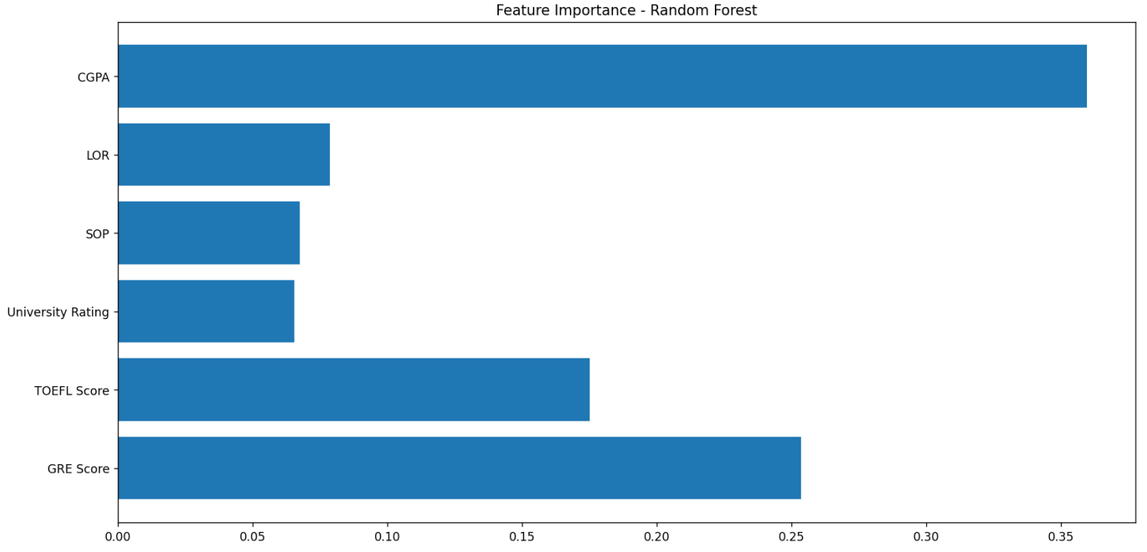
```
import matplotlib.pyplot as plt

plt.barh(X_train.columns,
         tree_model.feature_importances_)
plt.title('Feature Importance - Decision Tree')
plt.show()
```

```
import matplotlib.pyplot as plt

plt.barh(X_train.columns,
         forest_model.feature_importances_)
plt.title('Feature Importance - Random Forest')
plt.show()
```





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