Explainability metrics

EXPLAINABLE AI IN PYTHON

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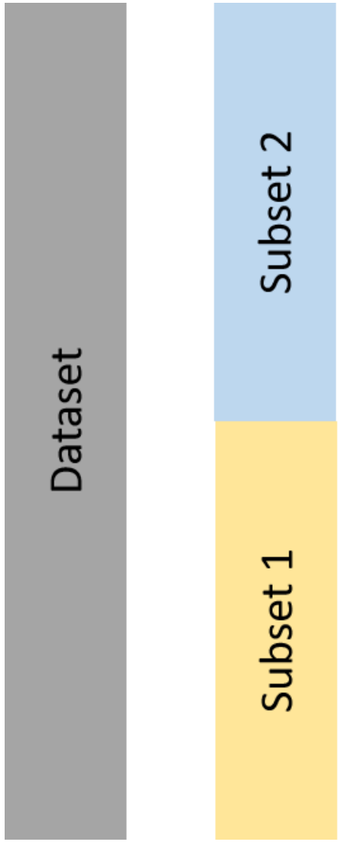
Machine Learning Engineer

datacamp

Consistency

- Assesses stability of explanations when model trained on different subsets
- Low consistency → no robust explanations



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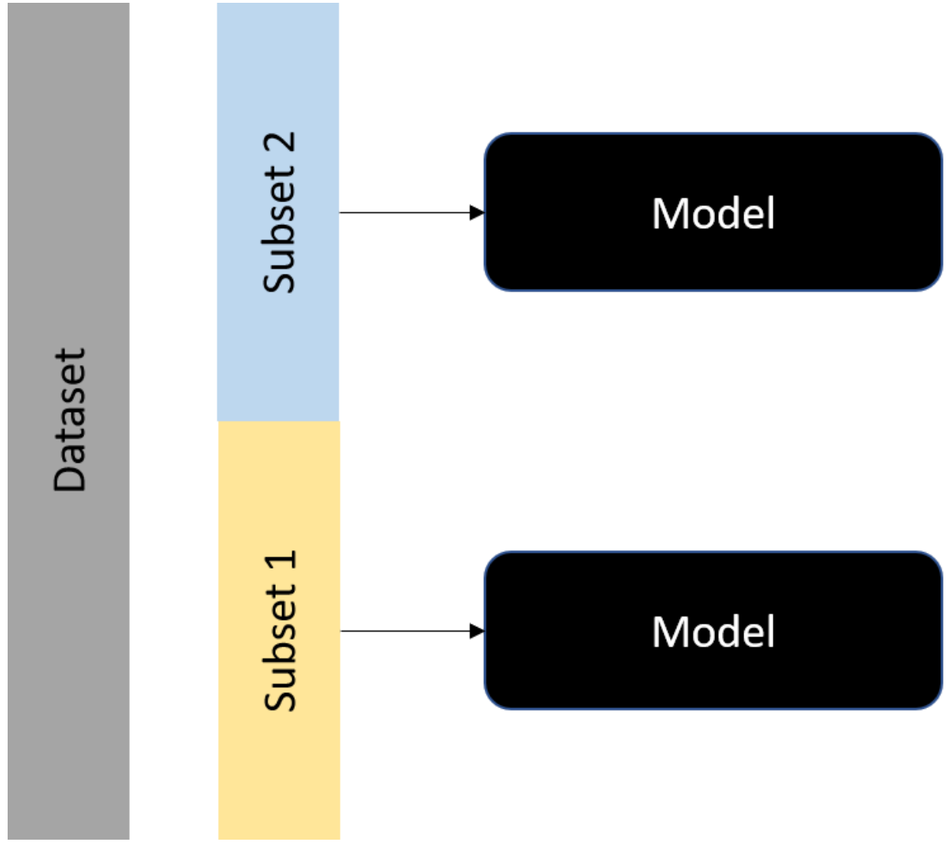

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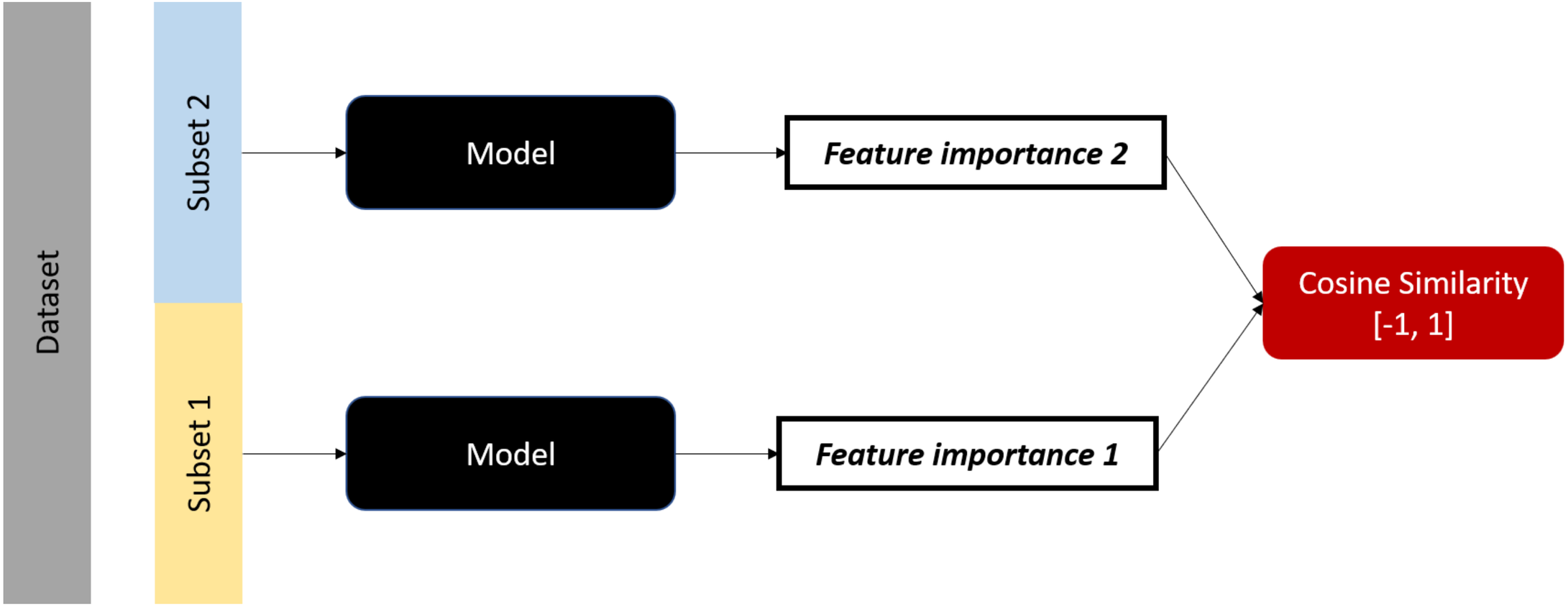
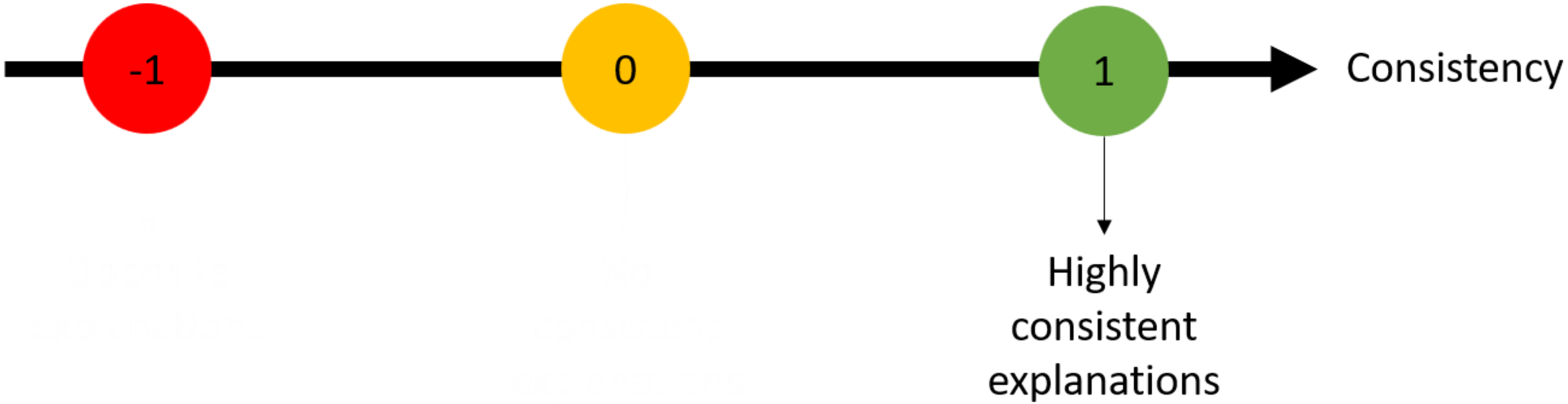


Cosine similarity to measure consistency



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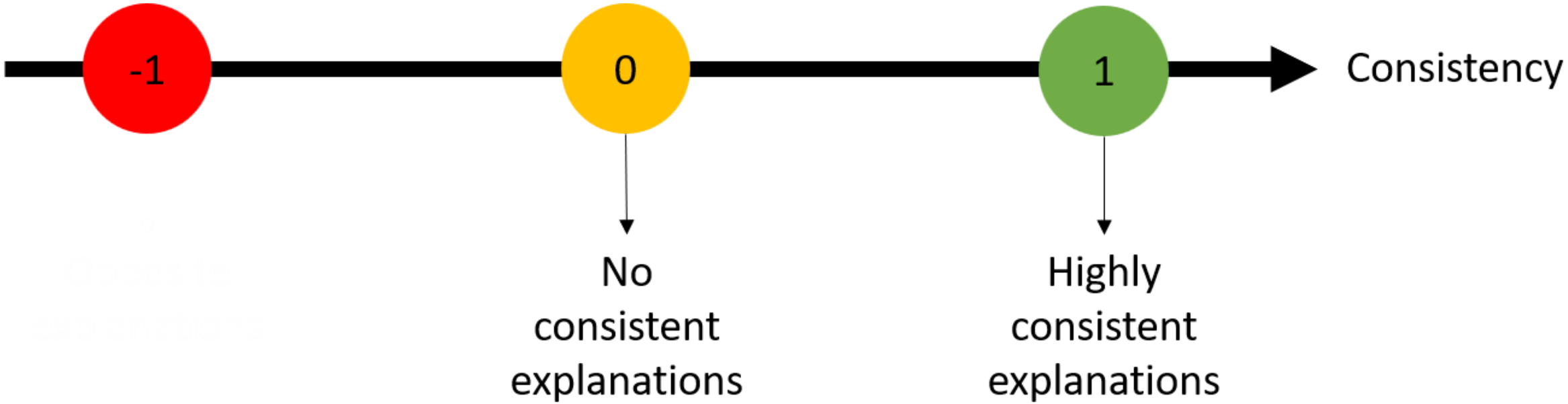

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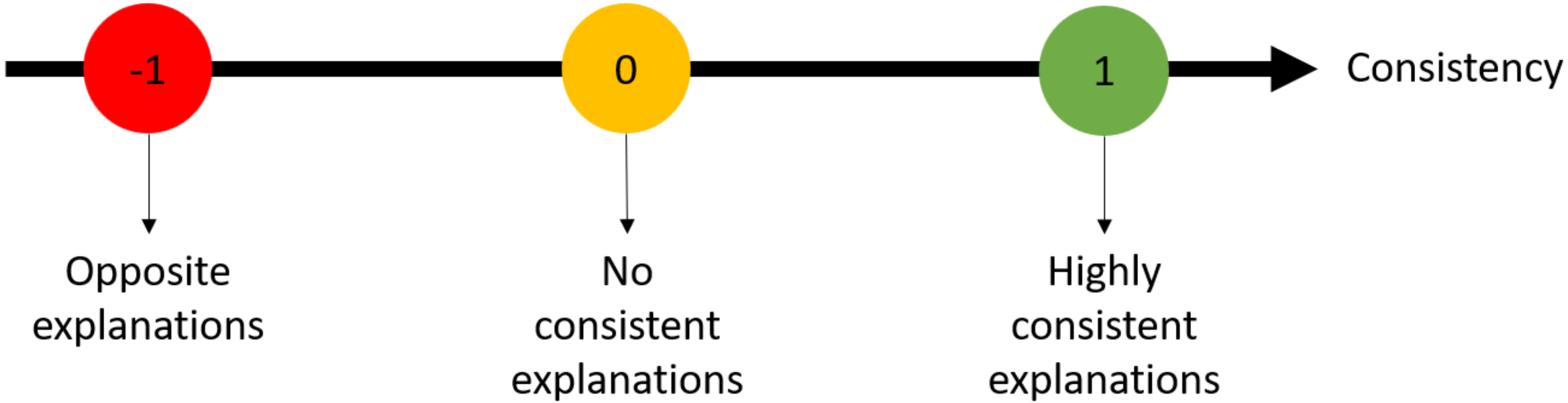

Admissions dataset

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

- `X1` , `y1` : first part of the dataset
- `X2` , `y2` : second part of the dataset
- `model1` , `model2` : random forest regressors

Computing consistency

```
from sklearn.metrics.pairwise import cosine_similarity

explainer1 = shap.TreeExplainer(model1)
explainer2 = shap.TreeExplainer(model2)

shap_values1 = explainer1.shap_values(X1)
shap_values2 = explainer2.shap_values(X2)

feature_importance1 = np.mean(np.abs(shap_values1), axis=0)
feature_importance2 = np.mean(np.abs(shap_values2), axis=0)

consistency = cosine_similarity([feature_importance1], [feature_importance2])
print("Consistency between SHAP values:", consistency)
```

```
Consistency between SHAP values: [[0.99706516]]
```

Faithfulness

- Evaluates if important features influence model's predictions
- Low faithfulness → misleads trust in model reasoning
- Useful in sensitive applications

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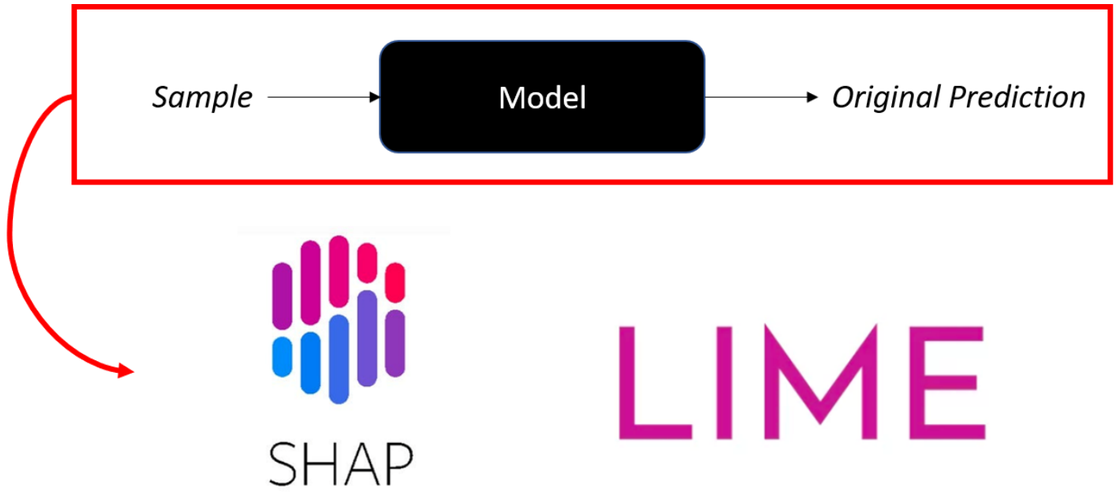

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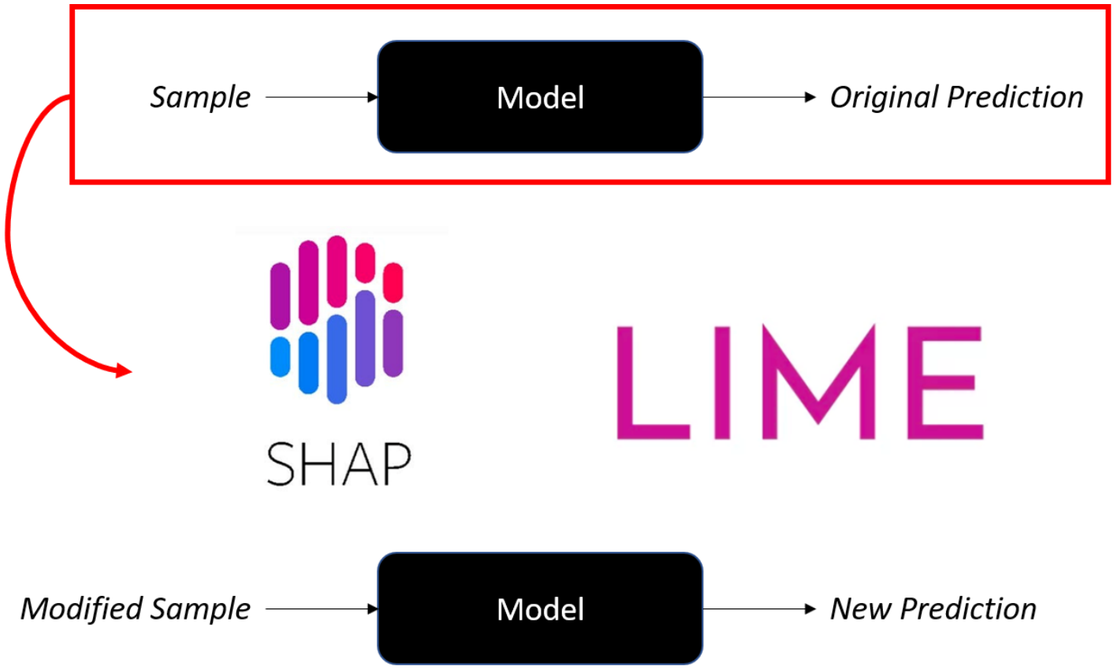

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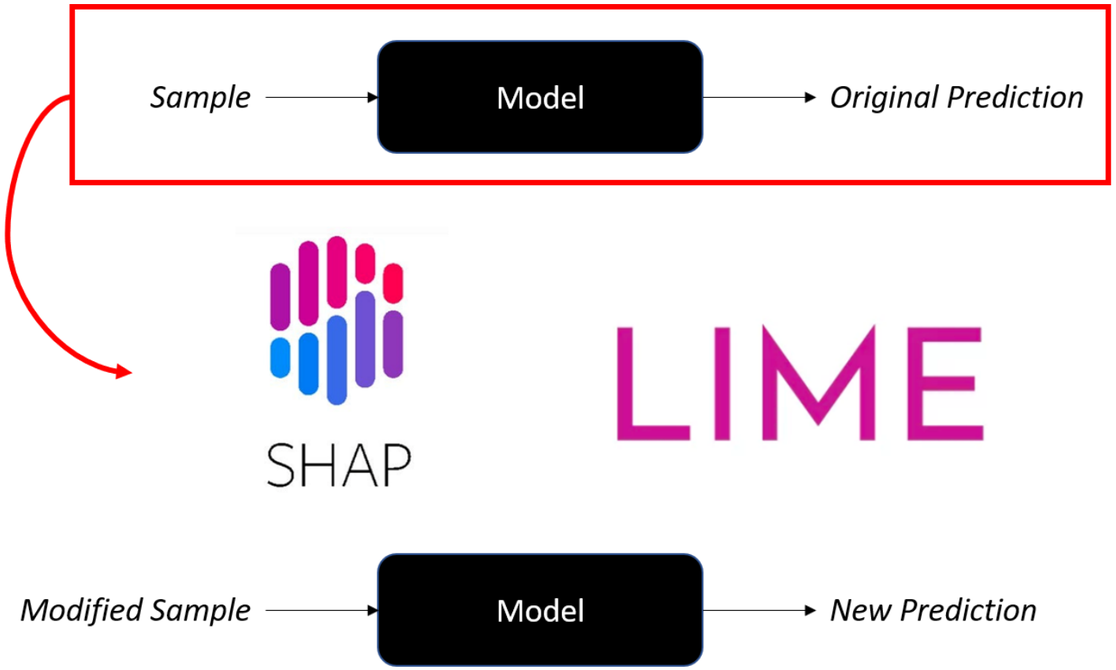
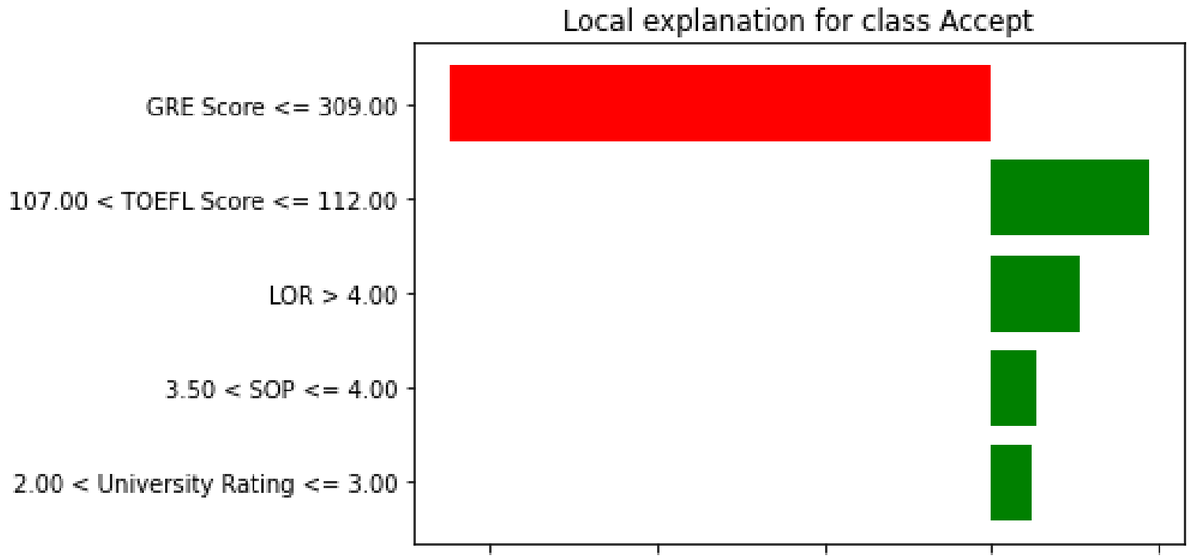


$$\boldsymbol{Faithfulness = Abs(New\ prediction\ - Original\ prediction)}$$

Computing faithfulness

```
X_instance = X_test.iloc[[0]]
original_prediction = model.predict_proba(X_instance)[0, 1]
print(f"Original prediction: {original_prediction}")
```

```
Original prediction: 0.43
```



Computing faithfulness

```
X_instance['GRE Score'] = 310

new_prediction = model.predict_proba(X_instance)[0, 1]
print(f"Prediction after perturbing {important_feature}: {new_prediction}")

faithfulness_score = np.abs(original_prediction - new_prediction)
print(f"Local Faithfulness Score: {faithfulness_score}")
```

```
Prediction after perturbing GRE Score: 0.77
Local Faithfulness Score: 0.34
```

Let's practice!

EXPLAINABLE AI IN PYTHON

Explaining unsupervised models

EXPLAINABLE AI IN PYTHON

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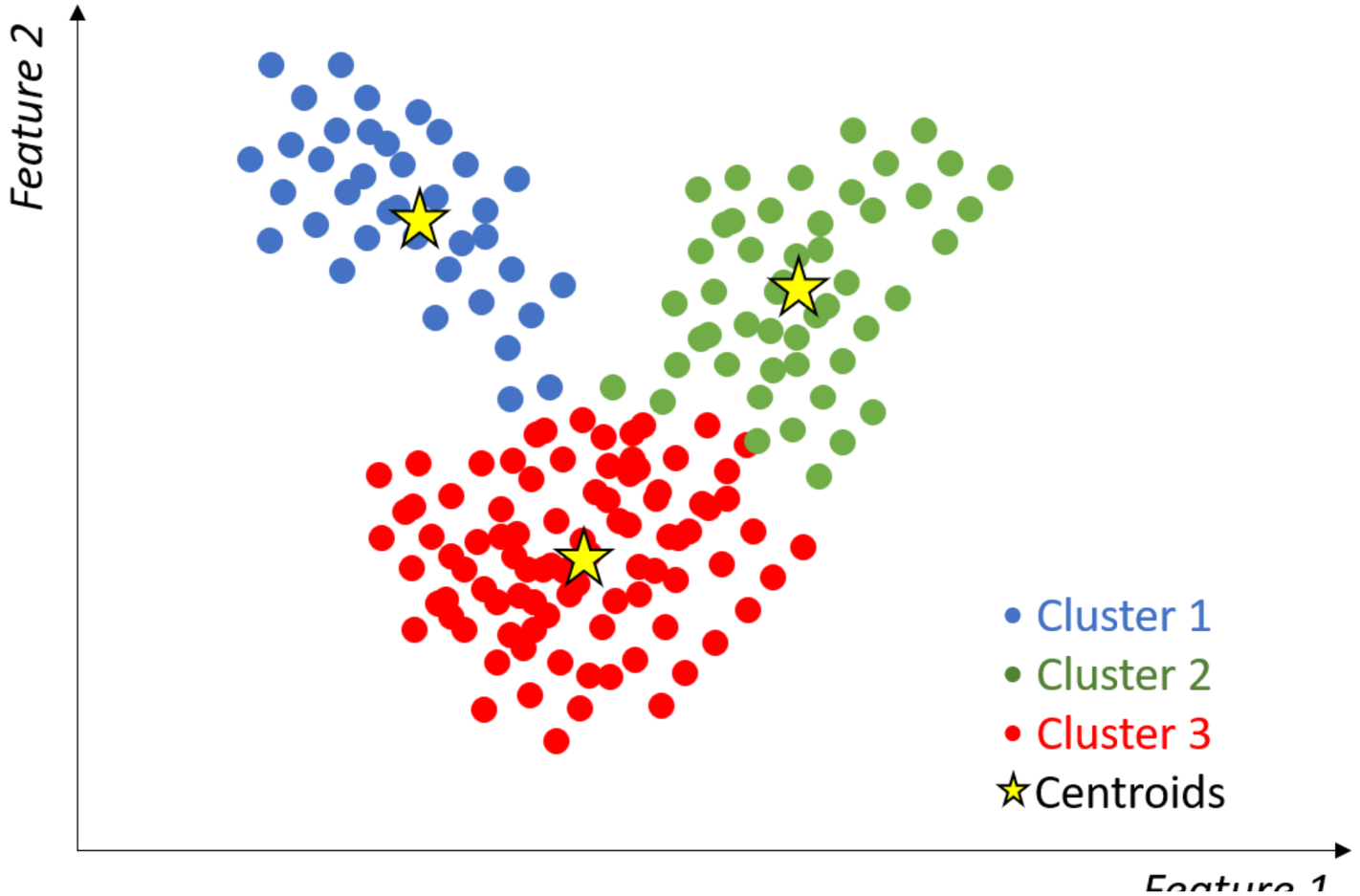
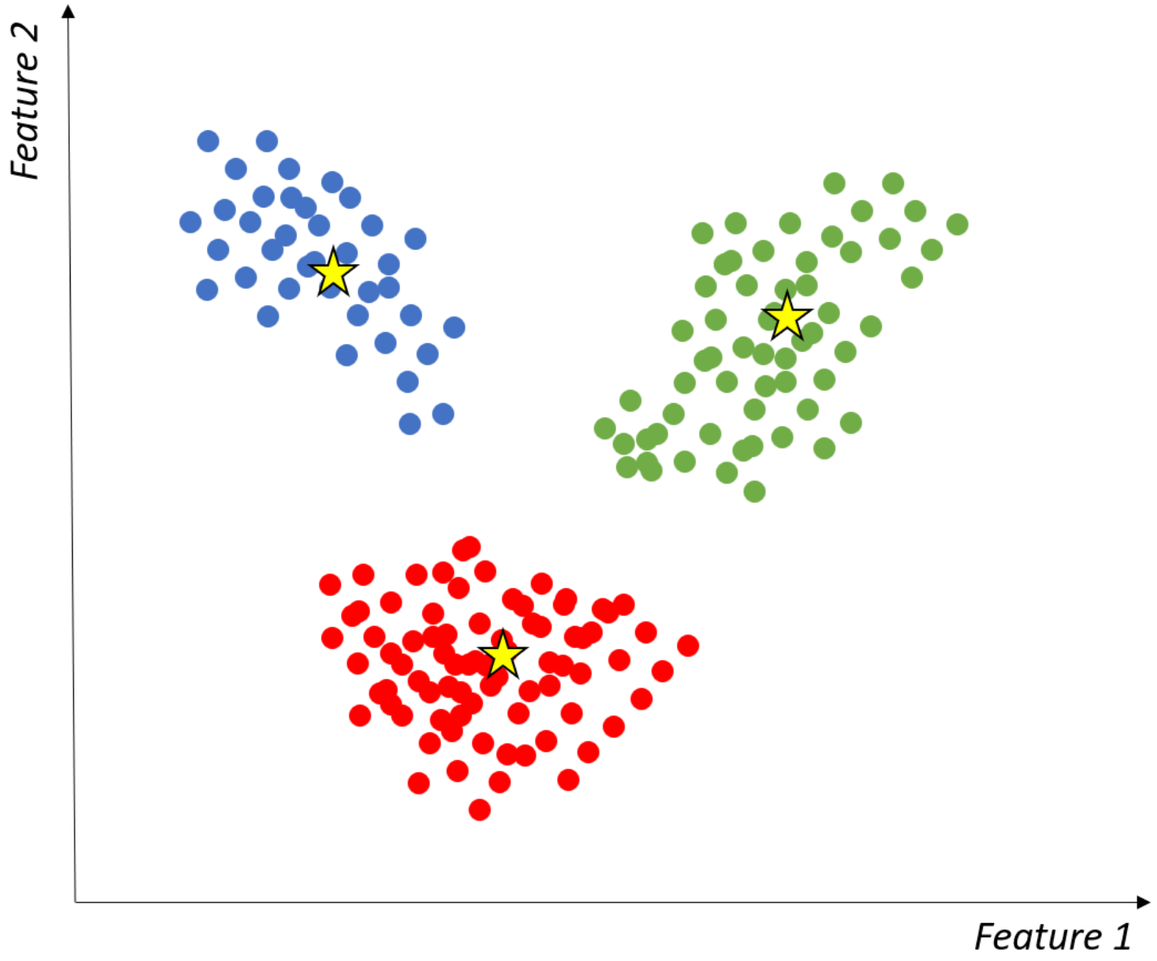
Clustering

Group similar data points without pre-defined labels



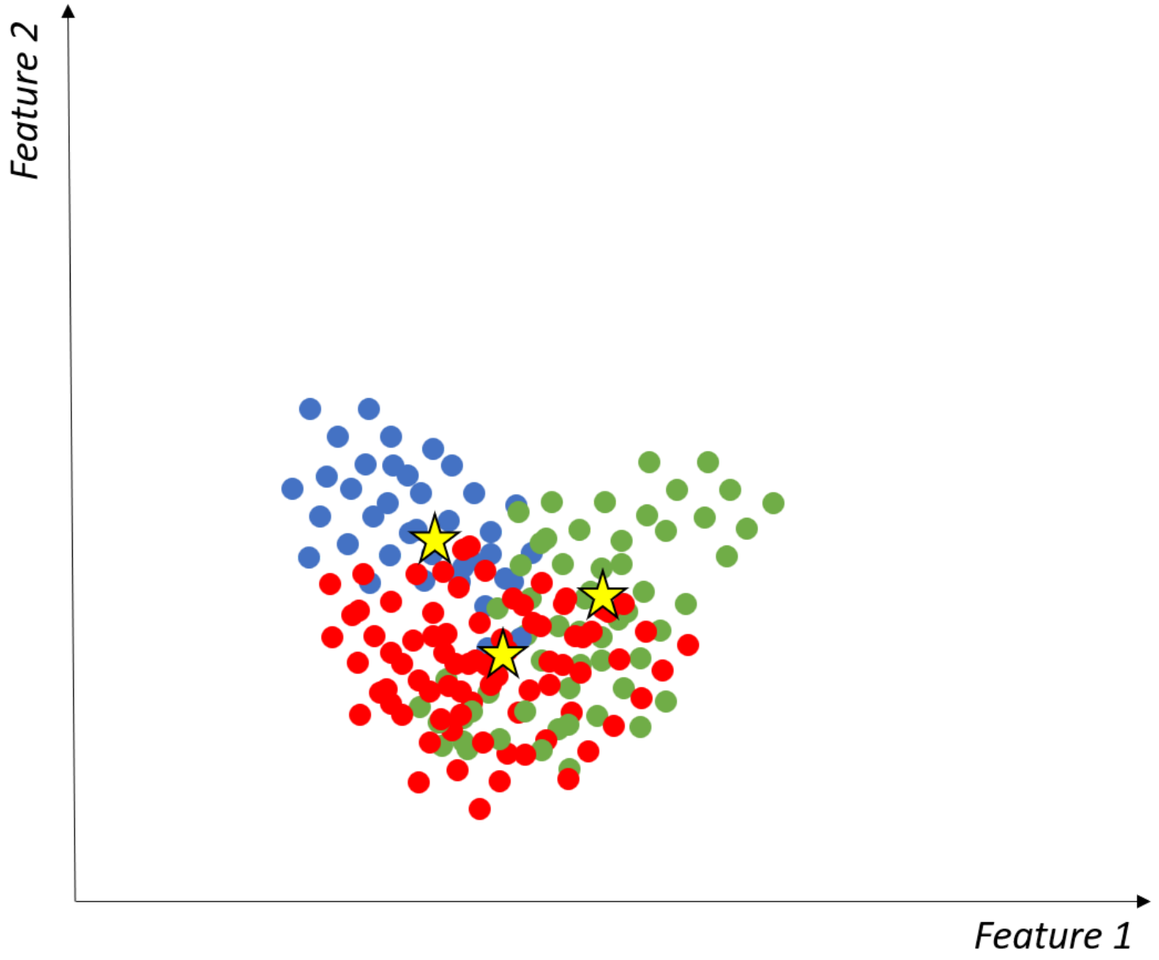
Silhouette score

- Measures clustering's quality
- Ranges from -1 to 1
  - 1 → well-separated clusters



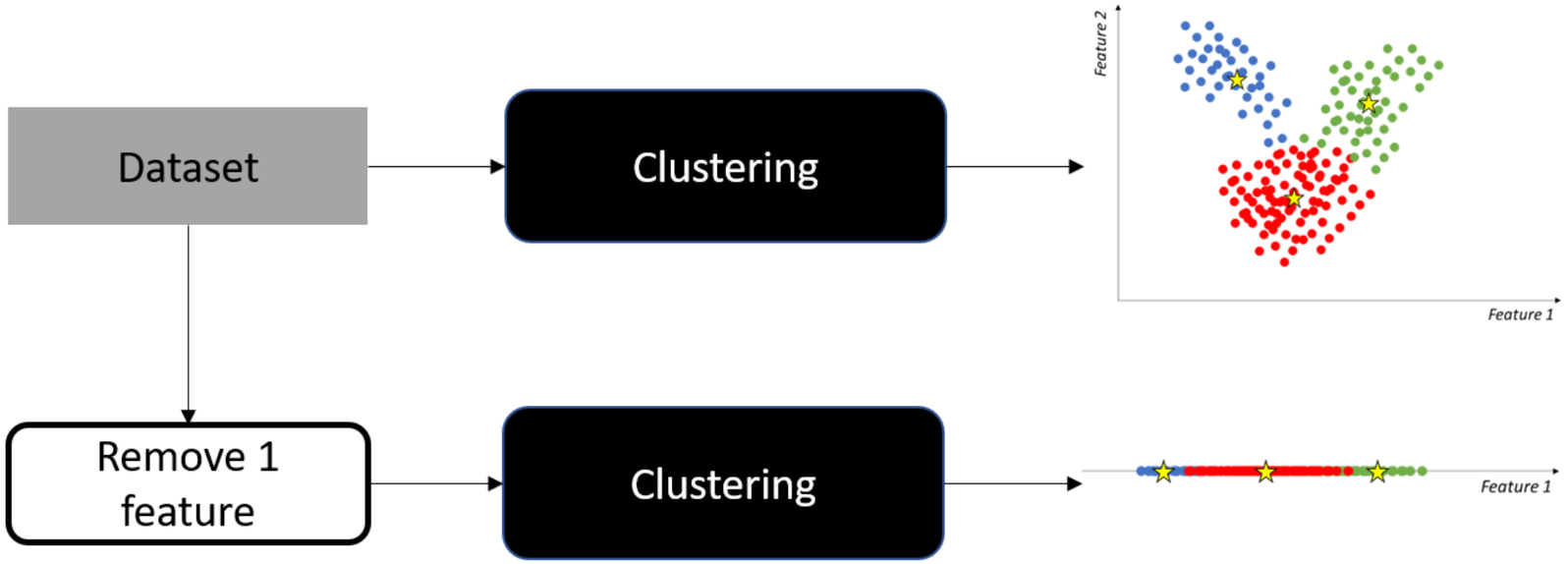
Silhouette score

- Measures clustering's quality
- Ranges from -1 to 1
  - 1 → well-separated clusters
  - -1 → points incorrectly assigned

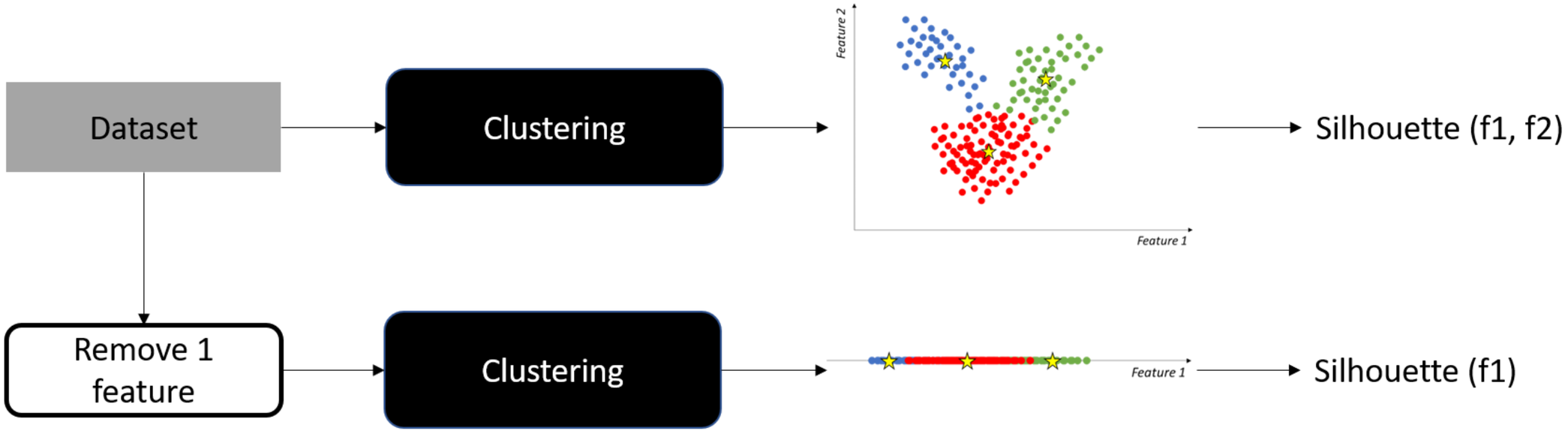


Feature impact on cluster quality

Feature impact on cluster quality



Feature impact on cluster quality



$$\boldsymbol{Impact\ (f2) = Silhouette\ (f1, f2) - Silhouette\ (f1)}$$

- $\mathrm{Impact}(f) > 0$ → positive contribution for f
- $\mathrm{Impact}(f) < 0$ → f introduces noise

Student Performance dataset

age	health status	absences	G1	G2	G3
18	3	4	0	11	11
17	3	2	9	11	11
15	3	6	12	13	12
15	5	0	14	14	14
16	5	0	11	13	13

`X` : array containing features

Computing feature impact on cluster quality

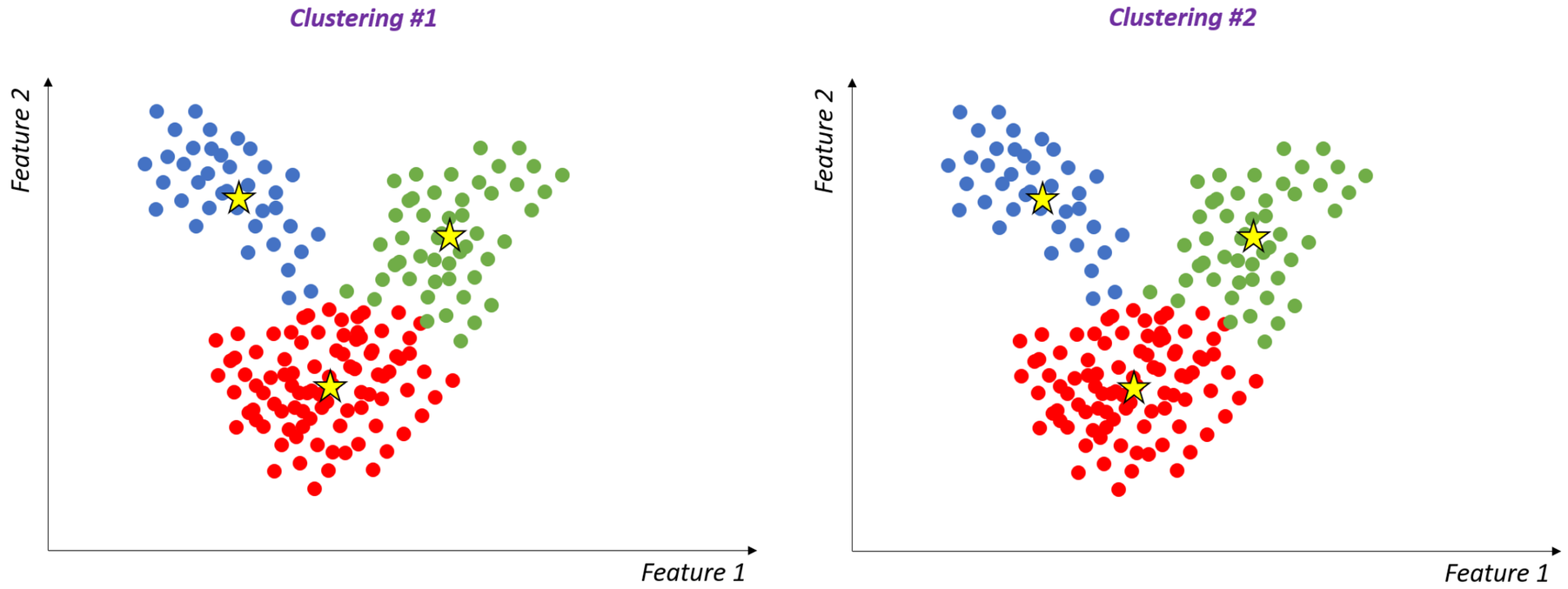
```
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

kmeans = KMeans(n_clusters=2).fit(X)
original_score = silhouette_score(X, kmeans.labels_)

for i in range(X.shape[1]):
    X_reduced = np.delete(X, i, axis=1)
    kmeans.fit(X_reduced)
    new_score = silhouette_score(X_reduced, kmeans.labels_)
    impact = original_score - new_score
    print(f'Feature {column_names[i]}: Impact = {impact}')
```

Computing feature impact on cluster quality

```
Feature age: Impact = 0.0519918166274128 1
Feature health status: Impact = 0.0604673742022763 8
Feature absences: Impact = 0.0312909405820266 94
Feature G1: Impact = -0.0257464219406523 53
Feature G2: Impact = -0.0257829233936411 9
Feature G3: Impact = -0.0316341945833015 8
```

Adjusted rand index (ARI)

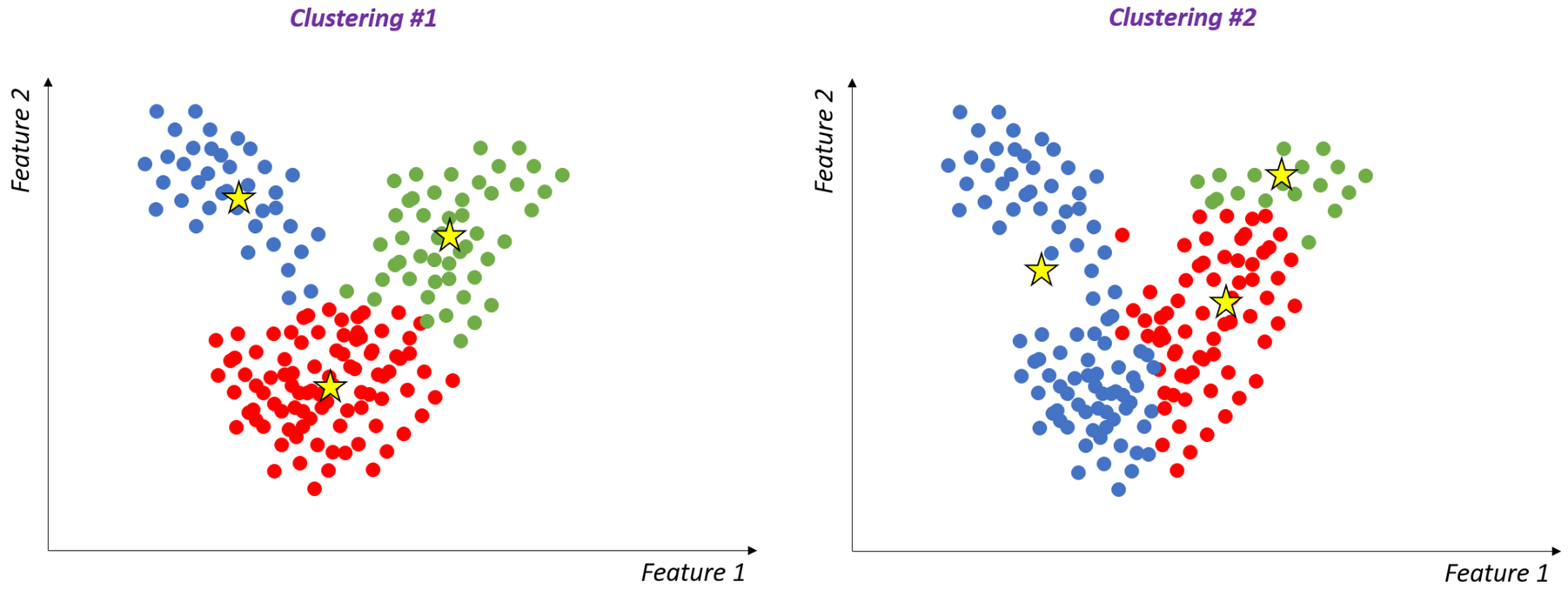
- Measures how well cluster assignments match



- Maximum ARI = 1 → perfect cluster alignment

Adjusted rand index (ARI)

- Measures how well cluster assignments match



- Maximum ARI = 1 → perfect cluster alignment
- Lower ARI → greater difference in clusterings

Feature importance for cluster assignments

- Remove features one at a time
- $\text{Importance}(f) = 1 - \text{ARI}\,(\text{original clusters, modifed clusters})$
- Low (ARI) → high $(1 - ARI)$ → important feature

Feature importance for cluster assignment

```
from sklearn.metrics import adjusted_rand_score

kmeans = KMeans(n_clusters=2).fit(X)
original_clusters = kmeans.predict(X)

for i in range(X.shape[1]):
    X_reduced = np.delete(X, i, axis=1)
    reduced_clusters = kmeans.fit_predict(X_reduced)
    importance = 1 - adjusted_rand_score(original_clusters, reduced_clusters)
    print(f'{df.columns[i]}: {importance}')
```

```
age: 0.0
health status: 0.9995376368119572
absences: 0.0
G1: 0.0
G2: 0.6204069909514572
G3: 0.6204069909514572
```

Let's practice!

EXPLAINABLE AI IN PYTHON

Explaining chat-based generative AI models

EXPLAINABLE AI IN PYTHON

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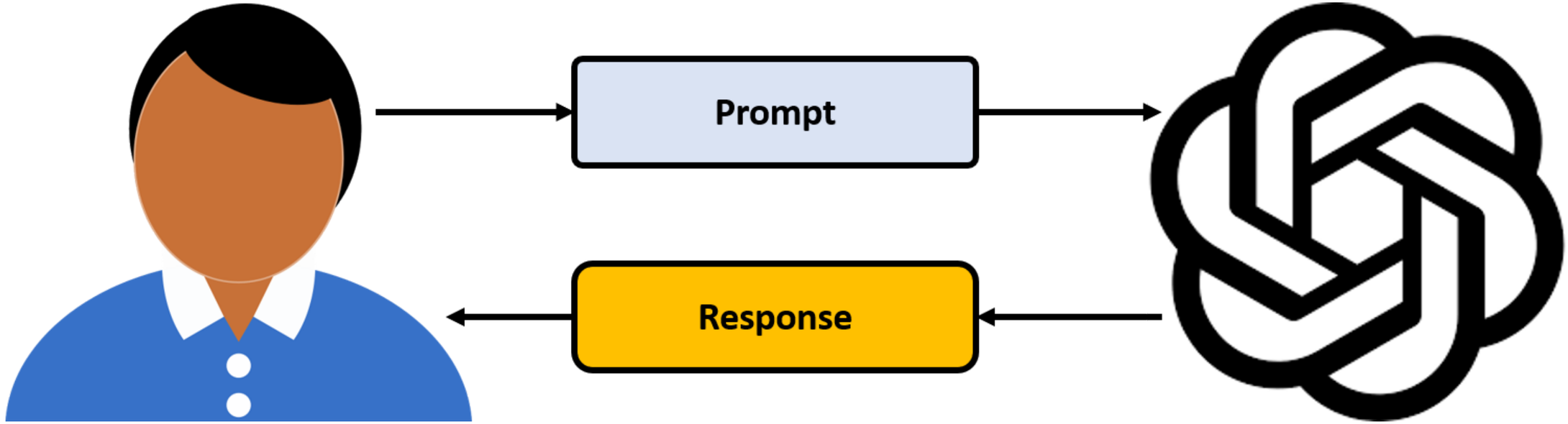
Machine Learning Engineer

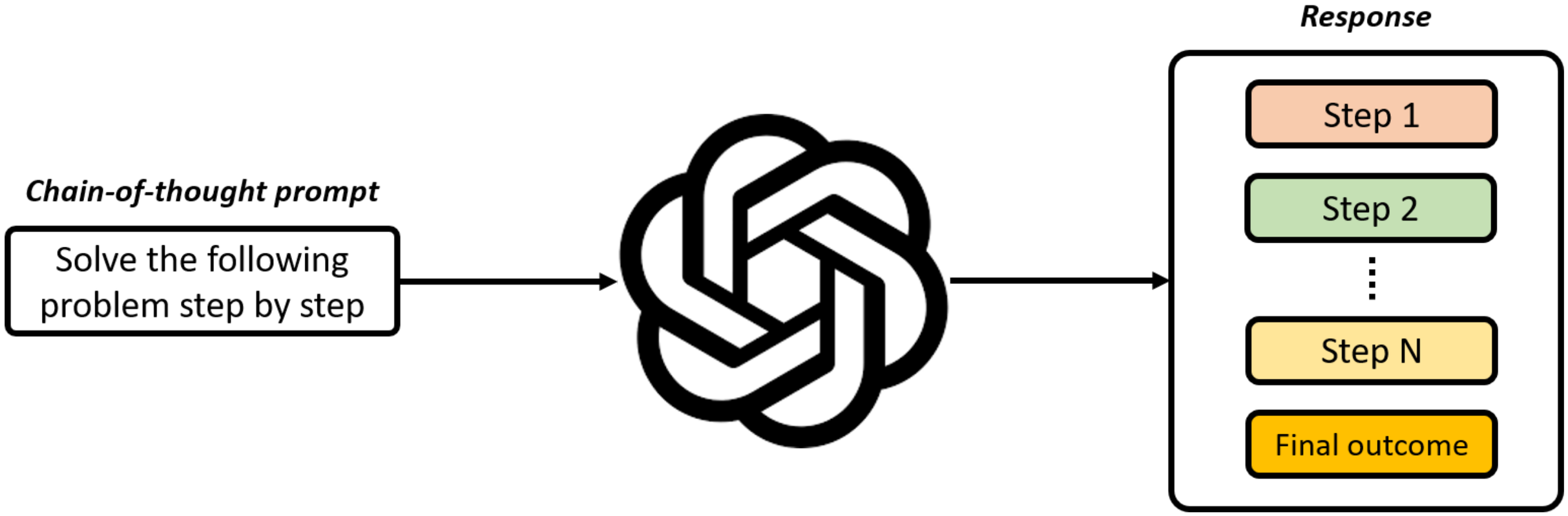
Chat-based generative AI models

- Used to generate text
- Predicts based on context and knowledge



Chain-of-thought prompt

- Encourages model to articulate its reasoning



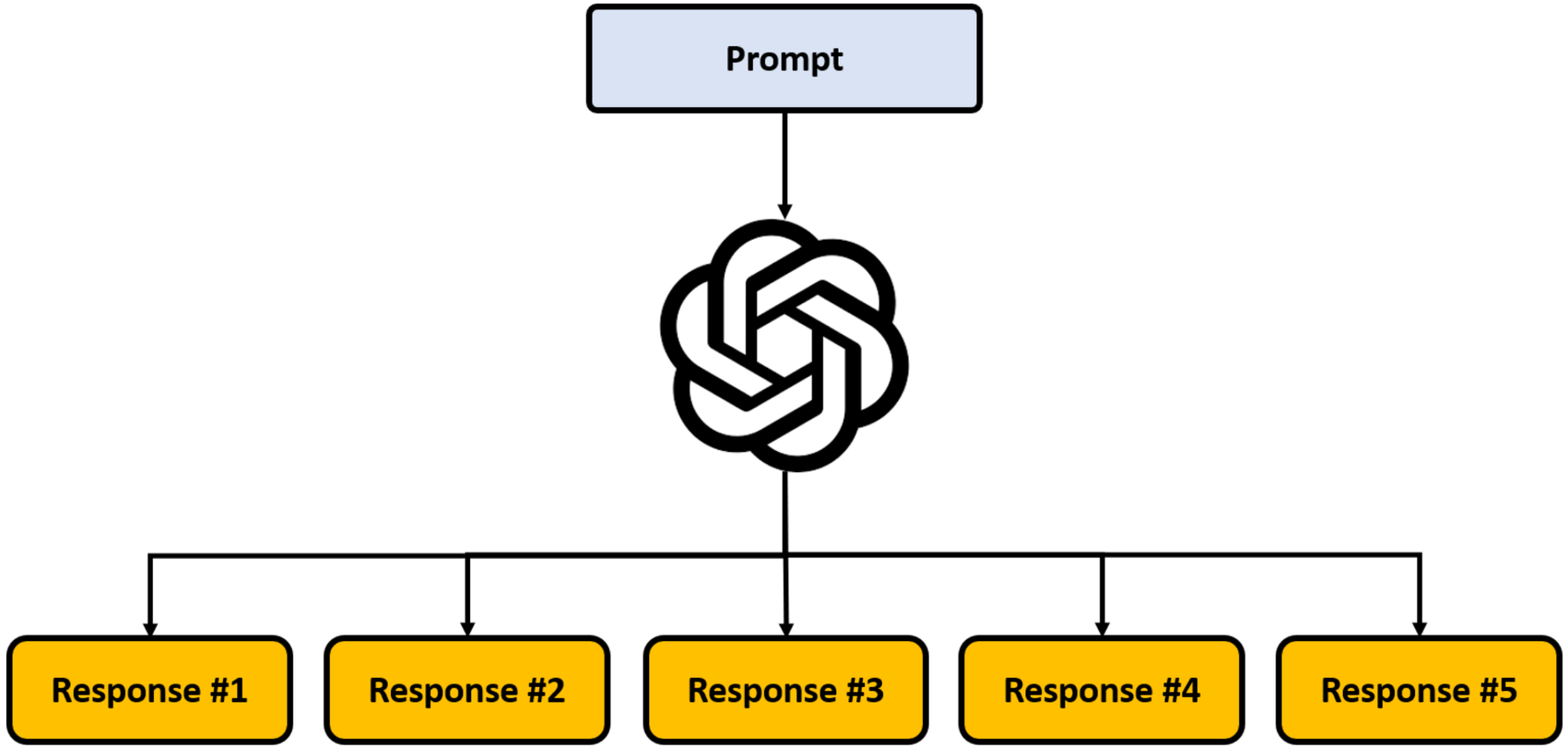
Creating a chain-of-thought prompt

```
prompt = """A shop starts with 20 apples. It sells 5 apples and then receives 8 more.
How many apples does the shop have now? Show your reasoning step-by-step."""
response = get_response(prompt)
print(response)
```

```
To find out how many apples the shop has now, let's follow the transactions step-by-step:
1- The shop begins with 20 apples.
2- The shop sells 5 apples.
   We subtract this number from the starting quantity: 20 - 5 = 15
3- The shop receives 8 apples.
   We add this number to the remaining apples: 15 + 8 = 23
So, after these transactions, the shop has 23 apples.
```

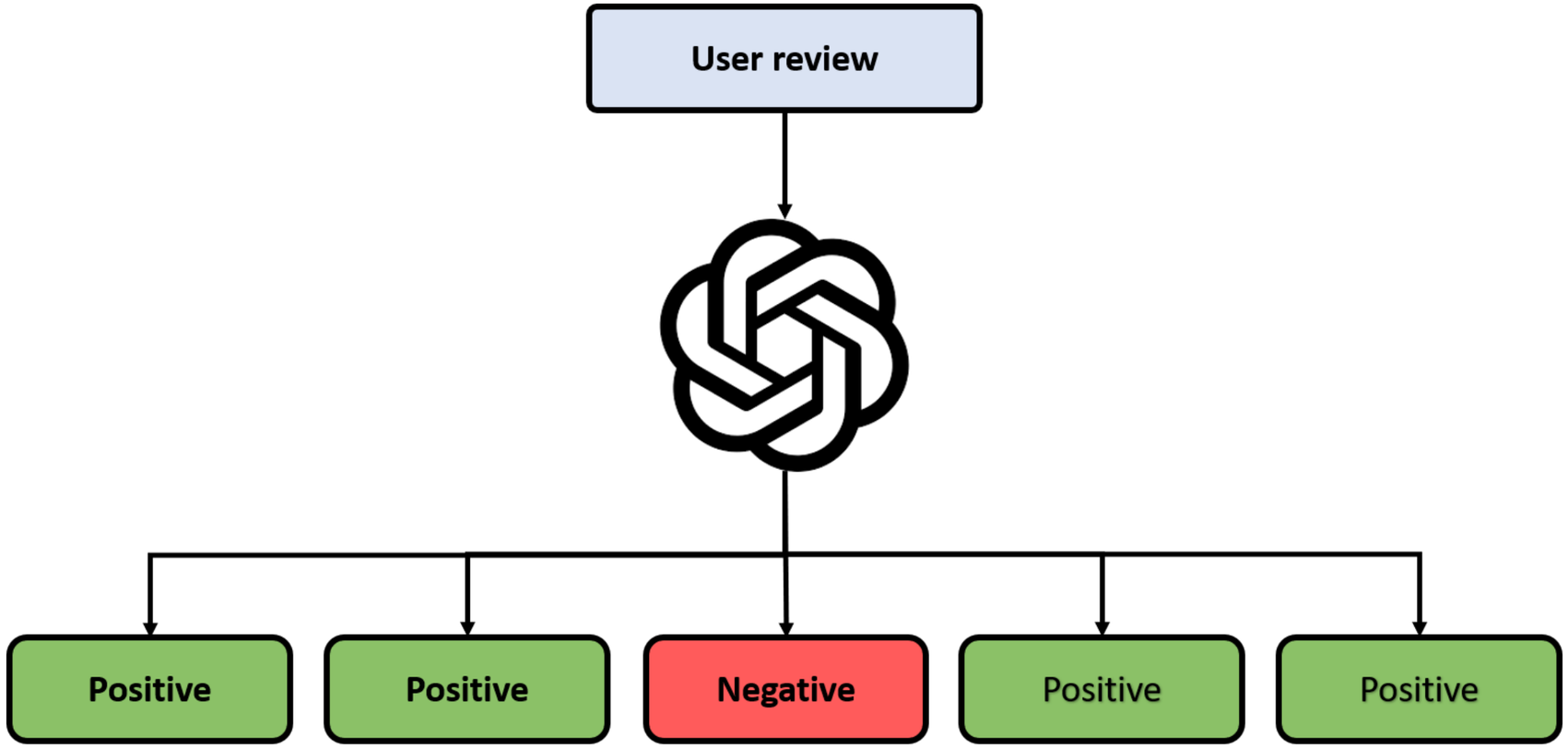
Self-consistency

Assesses model's confidence in generated answers



Self-consistency in text classification

Useful for text classification tasks



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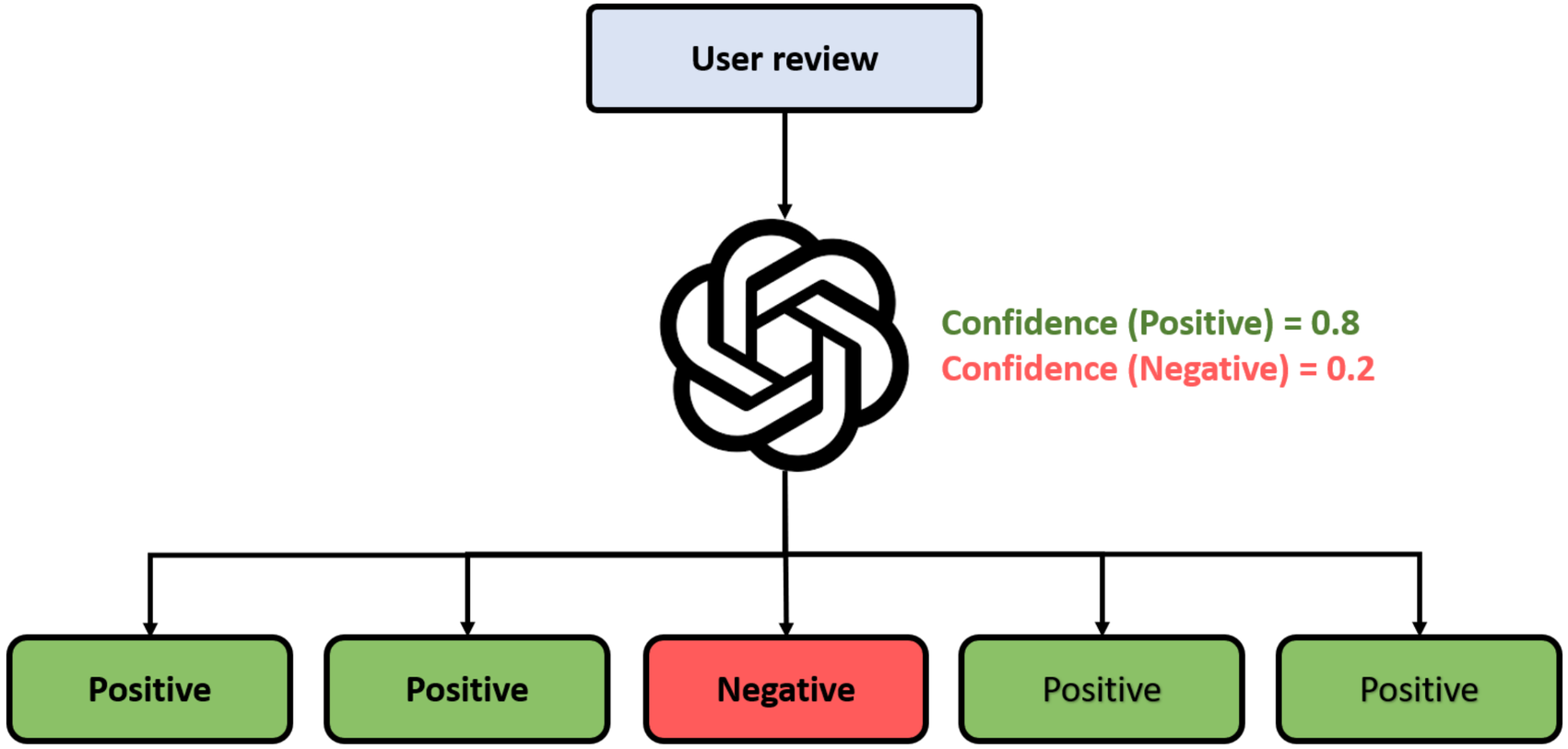

Creating self-consistency prompts

```
prompt = """Classify the following review as positive or negative.
You should reply with either "positive" or "negative", nothing else.
Review: 'The customer service was great, but the product itself did not meet my expectations.'"""

responses = []
for i in range(5):
    sentiment = get_response(review)
    responses.append(sentiment.lower())

confidence = {
    'positive': responses.count('positive') / len(responses),
    'negative': responses.count('negative') / len(responses)
}
```

Creating self-consistency prompts

```
print(confidence)
```

```
{
    'positive': 0.6,
    'negative': 0.4
}
```

Let's practice!

EXPLAINABLE AI IN PYTHON

Congratulations

EXPLAINABLE AI IN PYTHON

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Machine Learning Engineer

Chapter 1

Basics of explainable AI:

- Key principles and terminologies
- Model-specific explainability of linear and tree-based models

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Chapter 3

Local explainability:

- SHAP
- LIME

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Local explainability:

- SHAP
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Chapter 4

Advanced topics:

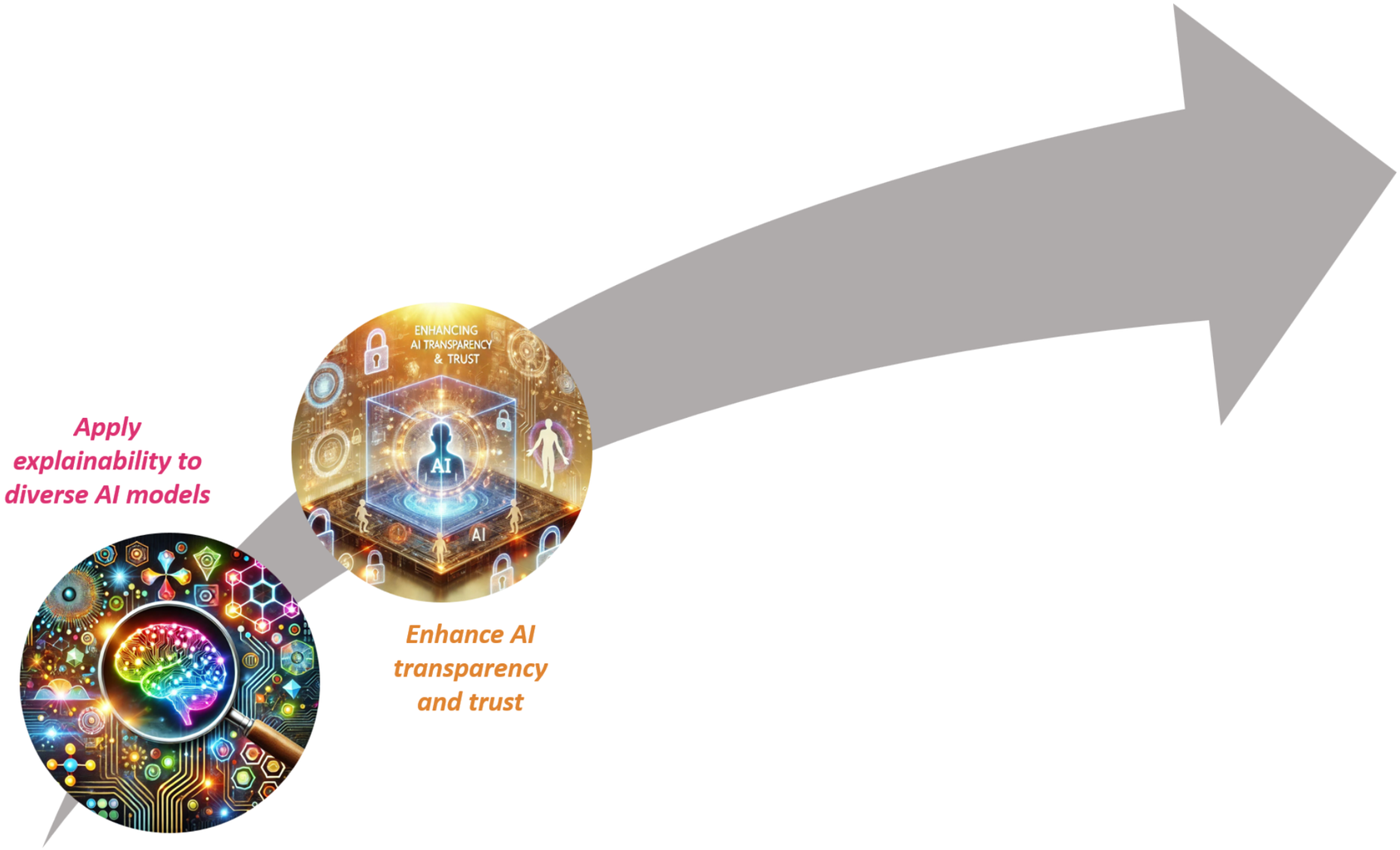
- Explainability metrics
- Explaining unsupervised models
- Explaining generative AI models

What's next?

Apply explainability to diverse AI models

[1] Images generated by DALL-E

What's next?



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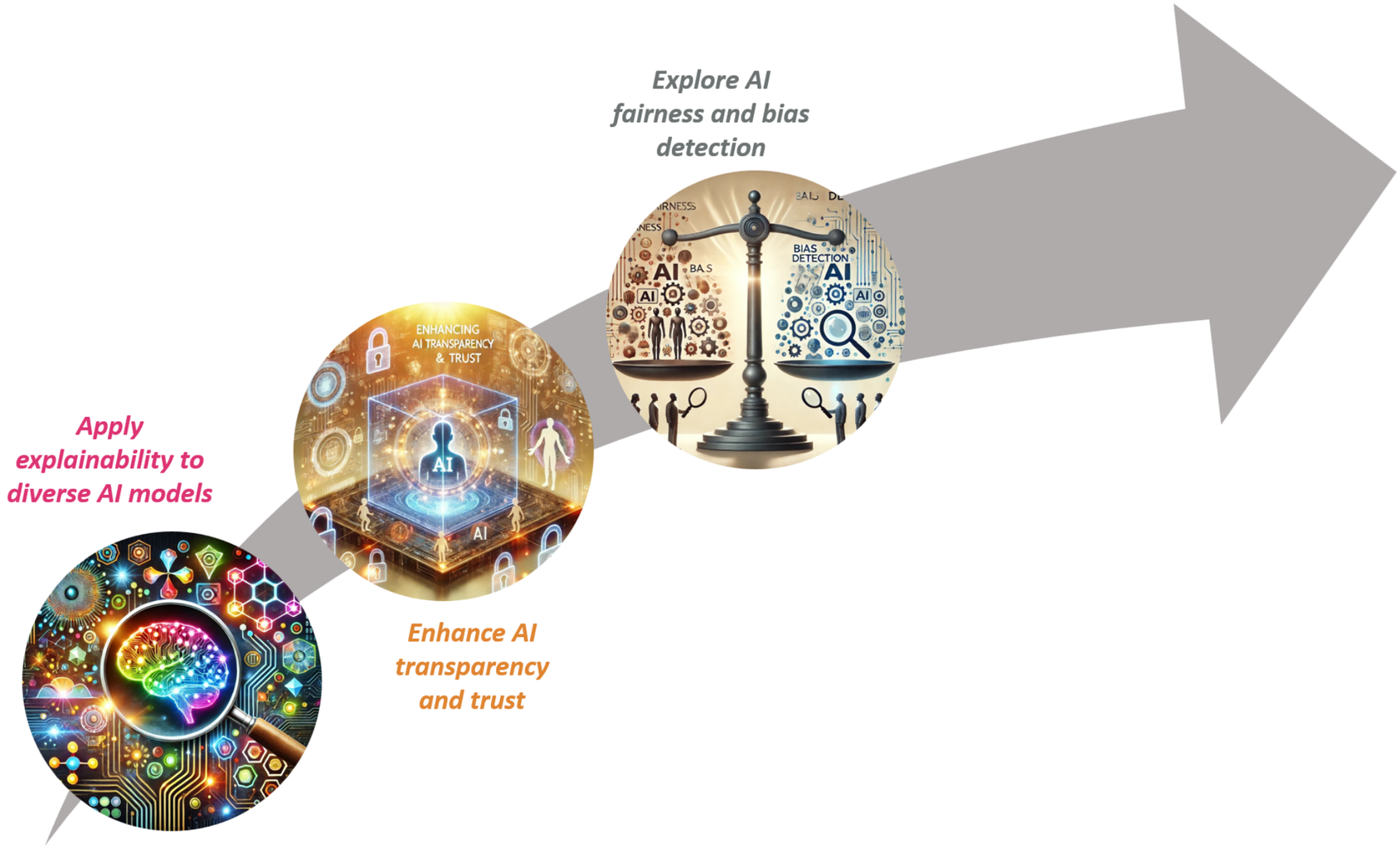

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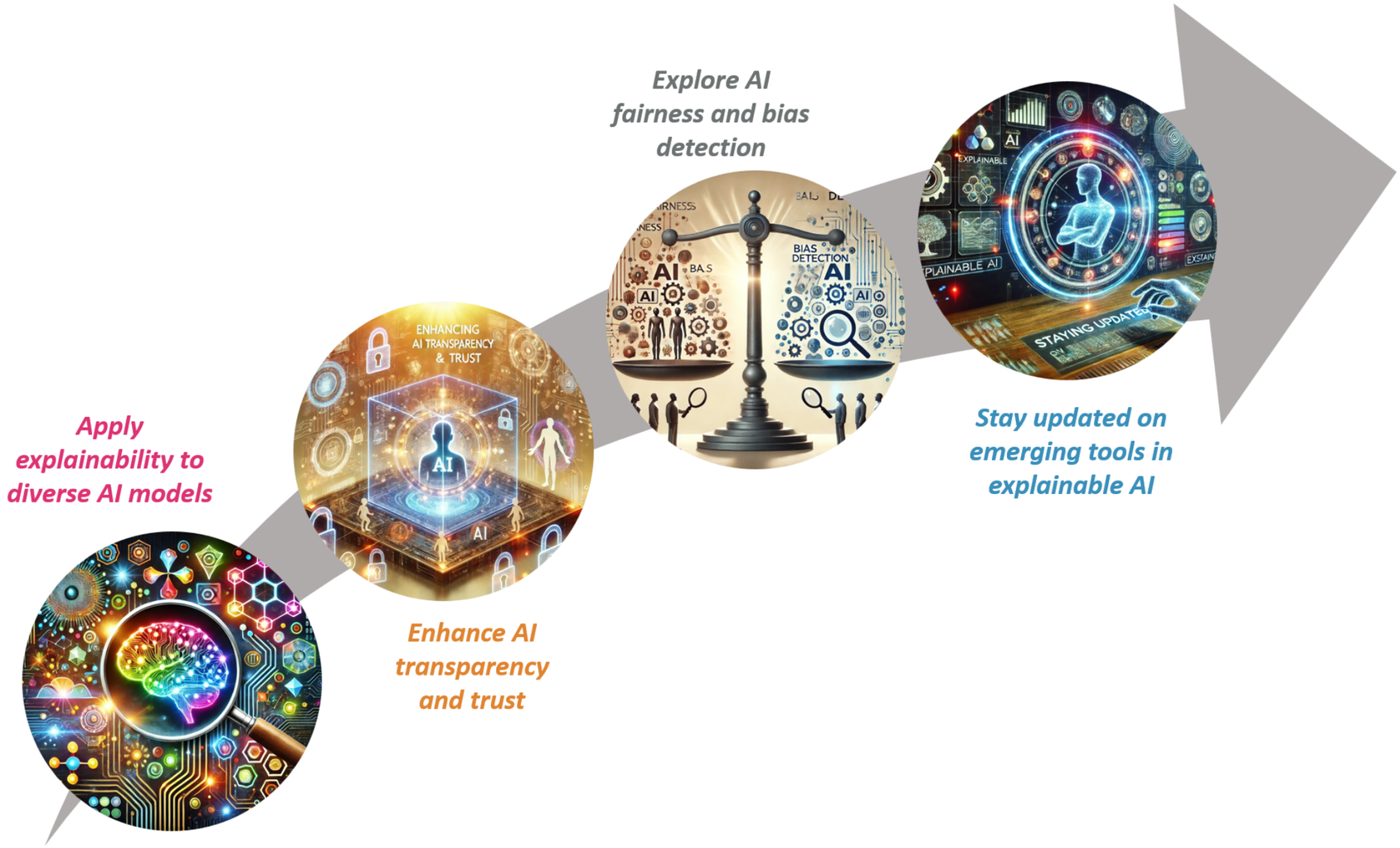

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Congratulations!

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