

The background of the slide is a complex, abstract pattern composed of numerous triangles in various shades of purple, blue, and black. The triangles are arranged in a way that creates a sense of depth and movement, with some triangles appearing to point towards the viewer and others away. The overall effect is a modern, digital aesthetic.

# AI LAB WEEK 8

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# NAÏVE BAYES' BASE THEOREM

- Bayes theorem is the cornerstone of Naïve Bayes Classifier because it provides a way to calculate the posterior probability  $P(h|D)$ , from the prior probability  $P(h)$ , together with  $P(D)$  and  $P(D|h)$ .

$$P(h|D) = \frac{P(D|h)P(h)}{P(D)} \xrightarrow{(P(D))} \text{Posterior probability}$$

$(P(D)) = P(Y) + P(N)$

D is the dataset and h is the hypothesis, for example yes/no  
The hypothesis which give the maximum value, you consider it as classification results.

# NAÏVE BAYES' BASE THEOREM

$$P(h|D) = \frac{P(D|h)P(h)}{P(D)} \longrightarrow \text{Posterior probability}$$

$$h_{MAP} \equiv \operatorname{argmax}_{h \in H} P(h|D) \quad \downarrow \text{maximum hypothesis}$$

$$= \operatorname{argmax}_{h \in H} \frac{P(D|h)P(h)}{\cancel{P(D)}}$$

$$= \operatorname{argmax}_{h \in H} P(D|h)P(h)$$

( P(D) is divided with every hypothesis )

# NAÏVE BAYES' BASE THEOREM

- The Bayesian approach to classifying the new instance is to assign the most probable target value,  $v_{MAP}$  given the attribute values  $\langle a_1, a_2 \dots a_n \rangle$  that describe the instance.

$$v_{MAP} = \operatorname{argmax}_{v_j \in V} P(v_j | a_1, a_2 \dots a_n)$$

- We can use Bayes theorem to rewrite this expression as

$$\begin{aligned} v_{MAP} &= \operatorname{argmax}_{v_j \in V} \frac{P(a_1, a_2 \dots a_n | v_j) P(v_j)}{\cancel{P(a_1, a_2 \dots a_n)}} \\ &= \operatorname{argmax}_{v_j \in V} P(a_1, a_2 \dots a_n | v_j) P(v_j) \end{aligned}$$

- Naïve Bayes Classifier:  $v_{NB} = \operatorname{argmax}_{v_j \in V} p(v_j) \prod_i p(a_i | v_j)$

hypothese

$$\begin{aligned} h_{MAP} &\equiv \operatorname{argmax}_{h \in H} P(h | D) \\ &= \operatorname{argmax}_{h \in H} \frac{P(D | h) P(h)}{P(D)} \\ &= \operatorname{argmax}_{h \in H} P(D | h) P(h) \end{aligned}$$

# NAÏVE BAYESIAN CLASSIFIER

```
import pandas as pd
from collections import defaultdict
data = {
'Day': ['D1', 'D2', 'D3', 'D4', 'D5', 'D6', 'D7', 'D8', 'D9', 'D10', 'D11', 'D12', 'D13', 'D14'],
'Outlook': ['Sunny', 'Sunny', 'Overcast', 'Rain', 'Rain', 'Rain', 'Overcast', 'Sunny', 'Sunny', 'Rain', 'Sunny', 'Overcast',
'Overcast', 'Rain'],
'Temp.': ['Hot', 'Hot', 'Hot', 'Mild', 'Cool', 'Cool', 'Cool', 'Mild', 'Cool', 'Mild', 'Mild', 'Mild', 'Hot', 'Mild'],
'Humidity': ['High', 'High', 'High', 'High', 'Normal', 'Normal', 'Normal', 'High', 'Normal', 'Normal', 'Normal', 'Normal', 'High',
'Normal', 'High'],
'Wind': ['Weak', 'Strong', 'Weak', 'Weak', 'Weak', 'Strong', 'Strong', 'Weak', 'Weak', 'Weak', 'Strong', 'Strong', 'Weak',
'Strong'],
'Decision': ['No', 'No', 'Yes', 'Yes', 'Yes', 'No', 'Yes', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'No']
}

df = pd.DataFrame(data)
```

# NAÏVE BAYESIAN CLASSIFIER

# Function to calculate probabilities

```
def calculate_probabilities(df):
```

```
    # Calculate prior probabilities
```

```
    total_instances = len(df)
```

```
    decision_counts = df['Decision'].value_counts()
```

```
    prior_prob_yes = decision_counts['Yes'] / total_instances
```

```
    prior_prob_no = decision_counts['No'] / total_instances
```

# NAÏVE BAYESIAN CLASSIFIER

```
# Calculate conditional probabilities
```

```
conditional_probs = defaultdict(dict)
```

```
for column in df.columns[1:-1]:
```

```
    # Exclude 'Day' and 'Decision' columns
```

```
    for value in df[column].unique():
```

```
        for decision in df['Decision'].unique():
```

```
            count = len(df[(df[column] == value) & (df['Decision'] == decision)])
```

```
            total_decision_count = decision_counts[decision]
```

```
            conditional_probs[column][(value, decision)] = count / total_decision_count
```

```
return prior_prob_yes, prior_prob_no, conditional_probs
```

# NAÏVE BAYESIAN CLASSIFIER

# Function to predict decision for new instance

```
def predict_decision(instance, prior_prob_yes, prior_prob_no, conditional_probs):
```

```
    prob_yes = prior_prob_yes
```

```
    prob_no = prior_prob_no
```

```
    for attr, value in instance.items():
```

```
        if attr != 'Decision':
```

```
            prob_yes *= conditional_probs[attr].get((value, 'Yes'), 0)
```

```
            prob_no *= conditional_probs[attr].get((value, 'No'), 0)
```

```
    return 'Yes' if prob_yes > prob_no else 'No'
```



# NAÏVE BAYESIAN CLASSIFIER

```
# Calculate probabilities
```

```
prior_prob_yes, prior_prob_no, conditional_probs = calculate_probabilities(df)
```

```
# Test with a new instance
```

```
new_instance = {'Outlook': 'Sunny', 'Temp.': 'Cool', 'Humidity': 'high', 'Wind': 'Strong'}
```

```
predicted_decision = predict_decision(new_instance, prior_prob_yes, prior_prob_no,  
conditional_probs)
```

```
print("Predicted decision for the new instance:", predicted_decision)
```

# TASKS

- #1: Implement the given dataset in list of list.**
- #2: Function to calculate probabilities (Prior Prob)**
- #3: Calculate conditional probabilities. (Posterior Prob)**
- #4: Function to predict decision for new instance**
- #5: Test with a new instance**