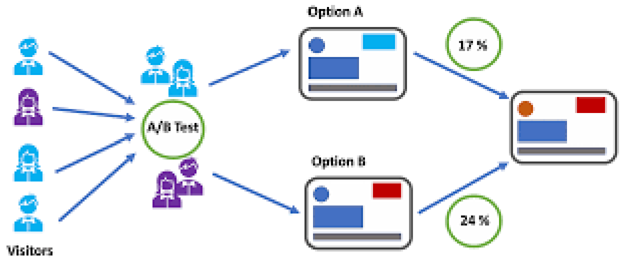
A/B Testing and Bandit Selection

A/B testing, also known as split testing or bucket testing, is a method for comparing two or more versions of a page or app to see which one performs better.



Bandit Selection refers to a class of algorithms known as multi-armed bandit algorithms that aim to solve the exploration-exploitation dilemma in decision-making problems. The term "multi-armed bandit" comes from the analogy of a gambler facing multiple slot machines ("one-armed bandits"), each with a different probability of payout, where the gambler must decide which machine to play in order to maximize their total reward over time.

Key Concepts:

1. **Exploration vs. Exploitation:**
    - **Exploration: Trying out different options (slot machines) to learn which one has the highest potential reward.**
    - **Exploitation: Leveraging the current knowledge by repeatedly choosing the option that has provided the best reward so far.**
2. **Goal: The main goal of a bandit algorithm is to maximize the cumulative reward over time while minimizing the regret (the difference between the optimal strategy and the one taken by the algorithm).**

K-Fold Cross-Validation (K-Fold CV) is a technique used to assess the performance and generalizability of a machine learning model by dividing the dataset into K equally sized folds (subsets) and evaluating the model on different portions of the data.

Steps of K-Fold Cross-Validation:

1. **Shuffle the Dataset: Randomly shuffle the dataset to ensure each fold has a good mix of data points.**
2. **Split the Data into K Folds: Divide the dataset into K equally sized subsets, called "folds."**
3. **Training and Validation:**
    - **In each iteration, use one of the K folds as the validation set (test set), and the remaining K-1 folds as the training set.**
    - **Train the model on the training set and evaluate its performance on the validation set.**

4. **Repeat K Times:** Repeat this process K times, where each fold gets used as the validation set exactly once.
5. **Average the Results:** After K iterations, average the performance metric (e.g., accuracy, precision, etc.) across all folds to get an estimate of the model's generalization performance.

Choosing K:

- Common values for K are 5 or 10.
- For smaller datasets, a larger K (like 10) is preferred for better validation.
- For larger datasets, a smaller K (like 5) may be sufficient since there is already a good amount of data in both training and validation sets.

Stratified K-Fold Cross-Validation ensures balanced class distribution by splitting the data in a way that each fold maintains the same proportion of samples from each class as the overall dataset. Here's how it works step by step:

Step-by-Step Process:

1. **Original Dataset Distribution:**
   - Let's say you have a dataset with two classes: Class A (80%) and Class B (20%).
   - In a dataset with 100 samples, 80 belong to Class A and 20 belong to Class B.
2. **Stratified Sampling:**
   - When using standard K-Fold (without stratification), folds may contain an uneven distribution of classes. Some folds might have mostly Class A samples, while others might have mostly Class B, which could lead to biased training or evaluation.
   - Stratified K-Fold ensures that the proportion of Class A and Class B samples is the same in each fold. So, if you divide the dataset into 5 folds, each fold will contain approximately 80% Class A and 20% Class B samples.
3. **Folds Creation:**
   - Stratified K-Fold first looks at the overall distribution of classes.
   - Then, for each fold, it selects samples in such a way that the proportion of each class in each fold reflects the original class distribution.

Example:

If you're using 5-fold stratified cross-validation with a dataset of 100 samples (80 Class A, 20 Class B), each fold would have:

- **16 samples of Class A (80% of the fold) and**
- **4 samples of Class B (20% of the fold).**

This ensures that during each training and validation phase, the model sees data that represents the original class distribution, preventing class imbalance from distorting the learning process.