```python
import pandas as pd
import numpy as np
```

Problem - 1: Perform a classification task with knn from scratch.

1.Load the Dataset: • Read the dataset into a pandas DataFrame

```python
df = pd.read_csv('/content/drive/MyDrive/Copy of diabetes_.csv');
df.head(3)
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1

Next steps: Generate code with df New interactive sheet

[6] 0s

```python
#  Finding all datas
print(df.info())

print()## for spaces

# Finding Missing values
print(df.isnull().sum())

print()

# Finding Summary statistics
print(df.describe(include="all"))

print()

# Finding Shape
print(df.shape)

print()

# 6. finding names
print(df.columns)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   768 non-null    int64
 2   BloodPressure             768 non-null    int64
 3   SkinThickness             768 non-null    int64
 4   Insulin                   768 non-null    int64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
None

Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
```

```
       Pregnancies     Glucose  BloodPressure  SkinThickness     Insulin  \
count   768.000000  768.000000     768.000000     768.000000  768.000000
mean      3.845052  120.894531      69.105469      20.536458   79.799479
std       3.369578   31.972618      19.355807      15.952218  115.244002
min       0.000000    0.000000       0.000000       0.000000    0.000000
25%       1.000000   99.000000      62.000000       0.000000    0.000000
50%       3.000000  117.000000      72.000000      23.000000   30.500000
75%       6.000000  140.250000      80.000000      32.000000  127.250000
max      17.000000  199.000000     122.000000      99.000000  846.000000

              BMI  DiabetesPedigreeFunction         Age     Outcome
count  768.000000                768.000000  768.000000  768.000000
mean    31.992578                  0.471876   33.240885    0.348958
std      7.884160                  0.331329   11.760232    0.476951
min      0.000000                  0.078000   21.000000    0.000000
25%     27.300000                  0.243750   24.000000    0.000000
50%     32.000000                  0.372500   29.000000    0.000000
75%     36.600000                  0.626250   41.000000    1.000000
max     67.100000                  2.420000   81.000000    1.000000

(768, 9)

Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

2.Handle Missing Data: • Handle any missing values appropriately, either by dropping or imputing them based on the data.

[7] 0s

```
df.isnull().sum()#find missing data
```

	0
Pregnancies	0
Glucose	0
BloodPressure	0
SkinThickness	0
Insulin	0
BMI	0
DiabetesPedigreeFunction	0
Age	0
Outcome	0

dtype: int64

```
# Clean column names
df.columns = df.columns.str.strip().str.lower()

# Drop unwanted columns safely
df = df.drop(
    columns=["bp.2s", "bp.2d", "location", "id", "chol", "stab.glu",
             "hdl", "glyhb", "bp.1s", "bp.1d", "time.ppn", "age"],
    errors="ignore"
)

# Handle frame column
if "frame" in df.columns:
    df["frame"] = df["frame"].fillna(df["frame"].mode()[0])
    df["frame"] = df["frame"].map({"small": 0, "medium": 1, "large": 2})

# Handle gender column
if "gender" in df.columns:
    df["gender"] = df["gender"].map({"male": 0, "female": 1})

# Fill numeric columns with median
num_cols = ["ratio", "height", "weight", "waist", "hip"]
for col in num_cols:
```

```python
# Fill numeric columns with median
num_cols = ["ratio", "height", "weight", "waist", "hip"]
for col in num_cols:
    if col in df.columns:
        df[col] = df[col].fillna(df[col].median())

df.head()
```

	pregnancies	glucose	bloodpressure	skinthickness	insulin	bmi	diabetespedigreefunction	outcome
0	6	148	72	35	0	33.6	0.627	1
1	1	85	66	29	0	26.6	0.351	0
2	8	183	64	0	0	23.3	0.672	1
3	1	89	66	23	94	28.1	0.167	0
4	0	137	40	35	168	43.1	2.288	1

Next steps: Generate code with df New interactive sheet

```python
df.isnull().sum()
```

	0
pregnancies	0
glucose	0
bloodpressure	0
skinthickness	0
insulin	0
bmi	0
diabetespedigreefunction	0
outcome	0

dtype: int64

```python
import numpy as np
import pandas as pd

# 1️⃣ Clean column names (safe habit)
df.columns = (
    df.columns
      .str.strip()
      .str.lower()
      .str.replace(" ", "_")
)

print("Columns in dataset:")
print(df.columns.tolist())

# 2️⃣ Separate FEATURES (X) and TARGET (y)
X = df.drop(columns=["outcome"]).values
y = df["outcome"].values

print("X shape:", X.shape)
print("y shape:", y.shape)
```

```
Columns in dataset:
```

```python
def train_test_split_scratch(X, y, test_size=0.3, random_seed=42):
    """
    Splits dataset into train and test sets from scratch.
    """

    np.random.seed(random_seed)

    # Generate array of indices
    indices = np.arange(X.shape[0])
    np.random.shuffle(indices)

    # Determine test size
    test_count = int(len(X) * test_size)

    # Split indices
    test_idx = indices[:test_count]
    train_idx = indices[test_count:]

    # Create train and test sets
    X_train = X[train_idx]
    X_test = X[test_idx]
    y_train = y[train_idx]
    y_test = y[test_idx]

    #Printing the results
```

```python
    #Printing the results
    print("X_train shape:", X_train.shape)
    print("X_test shape:", X_test.shape)
    print("y_train shape:", y_train.shape)
    print("y_test shape:", y_test.shape)

    return X_train, X_test, y_train, y_test

x_train, x_test, y_train, y_test = train_test_split_scratch(x, y)
```

```
X_train shape: (538, 0)
X_test shape: (230, 0)
y_train shape: (538,)
y_test shape: (230,)
```

4.Implement KNN: • Build the KNN algorithm from scratch (no libraries like sickit-learn for KNN).

• Compute distances using Euclidean distance.

• Write functions for:

– Predicting the class for a single query.

– Predicting classes for all test samples.

• Evaluate the performance using accuracy.

```python
def euclidean_distance(point1, point2):
    """
    Calculate the Euclidean distance between two points in n-dimensional space.

    Arguments:
    point1 : np.ndarray
        The first point as a numpy array.
    point2 : np.ndarray
        The second point as a numpy array.

    Returns:
    float
```

```
    The Euclidean distance between the two points.

    Raises:
    ValueError: If the input points do not have the same dimensionality.
    """

    if point1.shape != point2.shape:
        raise ValueError("Points must have the same dimensions to calculate Euclidean distance.")


    distance = np.sqrt(np.sum((point1 - point2) ** 2))
    return distance

euclidean_distance(x[0], x[1])
```

```
np.float64(0.0)
```

```
try:

    point1 = np.array([3, 4])
    point2 = np.array([0, 0])


    result = euclidean_distance(point1, point2)


    expected_result = 5.0
    assert np.isclose(result, expected_result), f"Expected {expected_result}, but got {result}"

    print("Test passed successfully!")
except ValueError as ve:
    print(f"ValueError: {ve}")
except AssertionError as ae:
    print(f"AssertionError: {ae}")
except Exception as e:
    print(f"An unexpected error occurred: {e}")
```

```
Test passed successfully!
```

```
try:
    X_test_sample = x_test[:5]
    y_test_sample = y_test[:5]


    predictions = knn_predict(X_test_sample, x_train, y_train, k=3)


    print("Predictions:", predictions)
    print("Actual labels:", y_test_sample)


    assert predictions.shape == y_test_sample.shape, (
        "The shape of predictions does not match the shape of the actual labels."
    )

    print("Test case passed successfully!")
except AssertionError as ae:
    print(f"AssertionError: {ae}")
except Exception as e:
    print(f"An unexpected error occurred: {e}")
```

```
Predictions: [1 1 1 1 1]
Actual labels: [0 0 0 0 0]
Test case passed successfully!
```

```python
    Returns:
    float
        The accuracy as a percentage (0 to 100).
    """
    correct_predictions = np.sum(y_true == y_pred)
    total_predictions = len(y_true)
    accuracy = (correct_predictions / total_predictions) * 100
    return accuracy



try:

    predictions = knn_predict(x_test, x_train, y_train, k=3)


    accuracy = compute_accuracy(y_test, predictions)


    print(f"Accuracy of the KNN model on the test set: {accuracy:.2f}%")
except Exception as e:
    print(f"An unexpected error occurred during prediction or accuracy computation: {e}")
```

```
Accuracy of the KNN model on the test set: 34.78%
```

```python
for k in [1, 3, 5, 7, 9, 11,13,15,16,17,18,20]:
    preds = knn_predict(x_test, x_train, y_train, k)
    acc = np.mean(preds == y_test)
    print(f"k = {k} -> Accuracy = {acc*100:.2f}%")
```

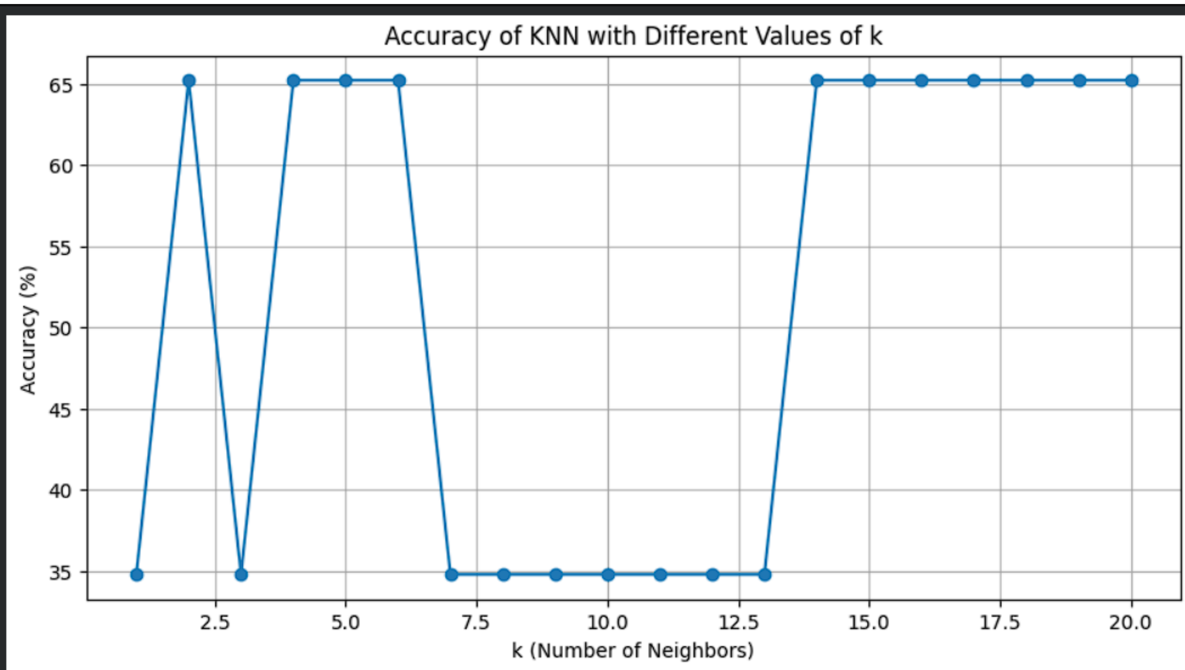
```
k = 1 -> Accuracy = 34.78%
k = 3 -> Accuracy = 34.78%
rl+Enter)     Accuracy = 65.22%
ed since last change     Accuracy = 34.78%
     Accuracy = 34.78%
y Prajwal Dulal     -> Accuracy = 34.78%
minutes ago)     -> Accuracy = 34.78%
10.196s
k = 15 -> Accuracy = 65.22%
k = 16 -> Accuracy = 65.22%
k = 17 -> Accuracy = 65.22%
k = 18 -> Accuracy = 65.22%
k = 20 -> Accuracy = 65.22%
```

```python
import matplotlib.pyplot as plt
def experiment_knn_k_values(X_train, y_train, X_test, y_test, k_values):
    """
    Run KNN predictions for different values of k and plot the accuracies.

    Arguments:
    X_train : np.ndarray
        The training feature matrix.
    y_train : np.ndarray
        The training labels.
    X_test : np.ndarray
        The test feature matrix.
    y_test : np.ndarray
        The test labels.
    k_values : list of int
        A list of k values to experiment with.

    Returns:
    dict
        A dictionary with k values as keys and their corresponding accuracies as values.
    """
    accuracies = {}

    for k in k_values:
```

```python
        predictions = knn_predict(X_test, X_train, y_train, k=k)
        accuracy = compute_accuracy(y_test, predictions)
        accuracies[k] = accuracy

        print(f"Accuracy for k={k}: {accuracy:.2f}%")


    plt.figure(figsize=(10, 5))
    plt.plot(k_values, list(accuracies.values()), marker='o')
    plt.xlabel('k (Number of Neighbors)')
    plt.ylabel('Accuracy (%)')
    plt.title('Accuracy of KNN with Different Values of k')
    plt.grid(True)
    plt.show()

    return accuracies


k_values = range(1, 21)


try:
    accuracies = experiment_knn_k_values(x_train, y_train, x_test, y_test, k_values)
    print("Experiment completed. Check the plot for the accuracy trend.")
```

```python
except Exception as e:
    print(f"An unexpected error occurred during the experiment: {e}")
```

```
Accuracy for k=1: 34.78%
Accuracy for k=2: 65.22%
Accuracy for k=3: 34.78%
Accuracy for k=4: 65.22%
Accuracy for k=5: 65.22%
Accuracy for k=6: 65.22%
Accuracy for k=7: 34.78%
Accuracy for k=8: 34.78%
Accuracy for k=9: 34.78%
Accuracy for k=10: 34.78%
Accuracy for k=11: 34.78%
Accuracy for k=12: 34.78%
Accuracy for k=13: 34.78%
Accuracy for k=14: 65.22%
Accuracy for k=15: 65.22%
Accuracy for k=16: 65.22%
Accuracy for k=17: 65.22%
Accuracy for k=18: 65.22%
Accuracy for k=19: 65.22%
Accuracy for k=20: 65.22%
```




```
Experiment completed. Check the plot for the accuracy trend
```

```python
def min_max_scale(X):
    """
    Manually scale the feature matrix X using min-max scaling.
    Returns the scaled version of X.
    """
    X_min = X.min(axis=0)        # minimum of each column
    X_max = X.max(axis=0)        # maximum of each column

    return (X - X_min) / (X_max - X_min)

x_scaled = min_max_scale(x)
x_scaled
```

```
array([], shape=(768, 0), dtype=float64)
```

```python
x_train_s, x_test_s, y_train_s, y_test_s = train_test_split_scratch(x_scaled, y)
```

```
X_train shape: (538, 0)
X_test shape: (230, 0)
y_train shape: (538,)
y_test shape: (230,)
```

```python
y_pred_scaled = knn_predict(x_test_s, x_train_s, y_train_s, k=3)
y_pred_scaled
```

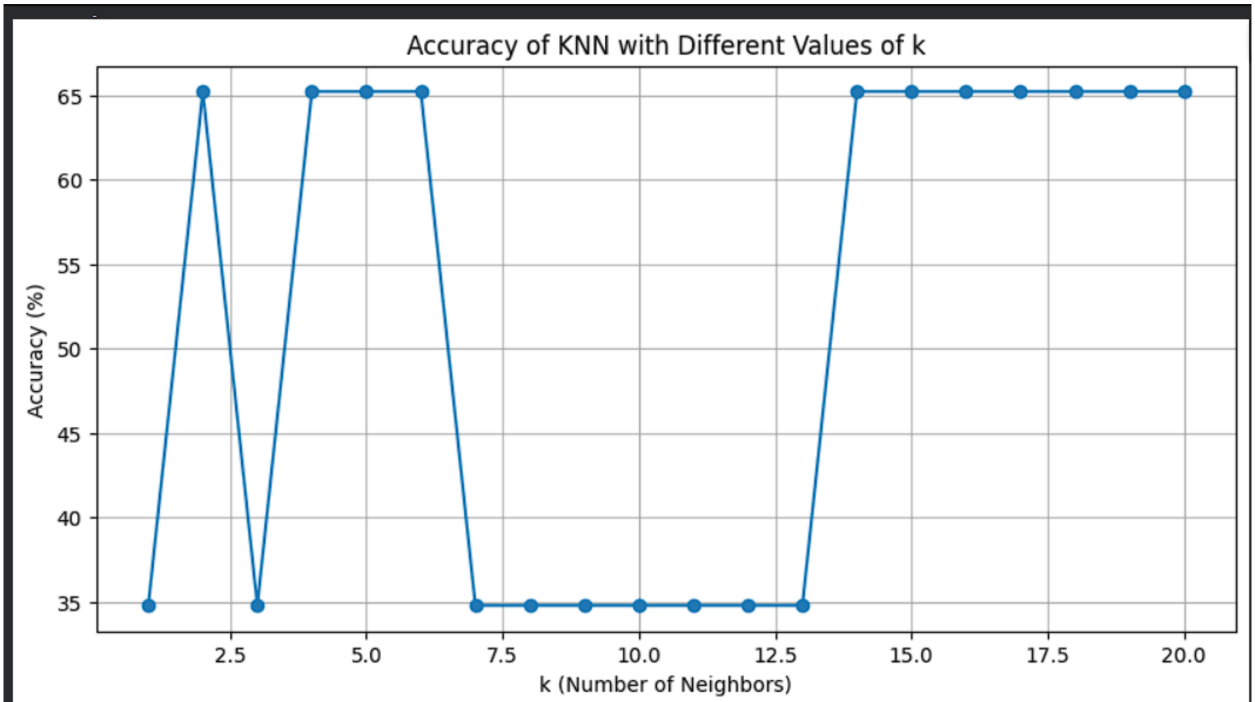
```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1])
```

```
accuracy_scaled = np.mean(y_pred_scaled == y_test_s)
accuracy_scaled
```

```
np.float64(0.34782608695652173)
```

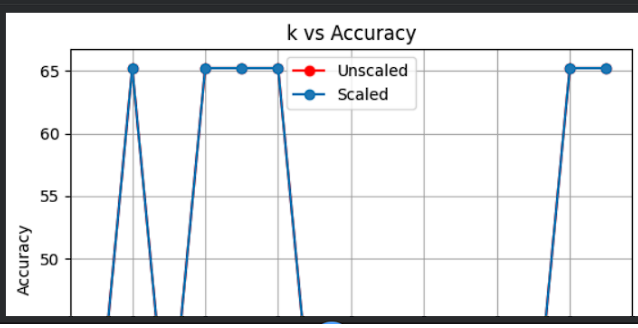
```
k_values = range(1, 21)
try:
    accuracies = experiment_knn_k_values(x_train_s, y_train_s, x_test_s, y_test_s, k_values)
    print("Experiment completed. Check the plot for the accuracy trend.")
except Exception as e:
    print(f"An unexpected error occurred during the experiment: {e}")
```

```
Accuracy for k=1: 34.78%
Accuracy for k=2: 65.22%
Accuracy for k=3: 34.78%
Accuracy for k=4: 65.22%
Accuracy for k=5: 65.22%
Accuracy for k=6: 65.22%
Accuracy for k=7: 34.78%
Accuracy for k=8: 34.78%
Accuracy for k=9: 34.78%
Accuracy for k=10: 34.78%
Accuracy for k=11: 34.78%
Accuracy for k=12: 34.78%
Accuracy for k=13: 34.78%
Accuracy for k=14: 65.22%
Accuracy for k=15: 65.22%
Accuracy for k=16: 65.22%
Accuracy for k=17: 65.22%
Accuracy for k=18: 65.22%
Accuracy for k=19: 65.22%
```



```python
import time

k_values = range(1, 16)

scaled_accuracy = []
unscaled_accuracy = []
time_unscaled = []
time_scaled = []

for kk in k_values:
    # Unscaled
    start = time.time()
    unscaled_pred = knn_predict(x_test, x_train, y_train, kk)
    end = time.time()

    unscaled_accuracy.append(compute_accuracy(y_test, unscaled_pred))
    time_unscaled.append(end - start)

    # Scaled
    start = time.time()
    scaled_pred = knn_predict(x_test_s, x_train_s, y_train, kk)
    end = time.time()

    scaled_accuracy.append(compute_accuracy(y_test, scaled_pred))
    time_scaled.append(end - start)
```

```python
plt.plot(k_values, unscaled_accuracy, marker='o', label='Unscaled', color='red')
plt.plot(k_values, scaled_accuracy, marker='o', label='Scaled')
plt.xlabel('k')
plt.ylabel('Accuracy')
plt.title('k vs Accuracy')
plt.legend()
plt.grid(True)
plt.show()
```



The accuracy of the KNN model is low and unstable for small values of k because the model is sensitive to noise. As k increases, accuracy improves since predictions are based on more neighbors, making them more stable. The scaled dataset consistently performs better than the unscaled dataset because scaling ensures fair distance calculations. The prediction time remains almost constant for all values of k, so increasing k does not significantly increase computational cost. Based on the plots, the optimal value of k lies around 13–15, where the scaled data achieves the highest accuracy with reasonable computation time.

Problem - 4 - Additional Questions {Optional - But Highly Recommended}: • Discuss the challenges of using KNN for large datasets and high-dimensional data. • Suggest strategies to improve the efficiency of KNN (e.g., approximate nearest neighbors, dimensionality reduction).

Challenges of using KNN for large datasets and high-dimensional data: KNN becomes computationally expensive for large datasets because it calculates distances between every test sample and all training samples. It also consumes a lot of memory as it stores all training data. For high-dimensional data, the “curse of dimensionality” makes distances less meaningful, causing predictions to become less accurate. Additionally, KNN is sensitive to irrelevant features and feature scales, which can further reduce its performance.

Strategies to improve KNN efficiency: Efficiency can be improved by using approximate nearest neighbor methods like KD-Trees or Ball Trees, which reduce the number of distance calculations. Dimensionality reduction techniques such as PCA can help simplify the feature space, making distances more meaningful and faster to compute. Feature scaling ensures no single feature dominates the distance metric, and selecting the optimal K through cross-validation improves accuracy. Clustering can also be used to limit search space for faster predictions.