Part 9

```
!!pip install lightgbm
```

```
from sklearn.datasets import load_svmlight_file
from sklearn.metrics import ndcg_score
import numpy as np

# Load the dataset for one fold
def load_one_fole(data_path):
    X_train, y_train, qid_train = load_svmlight_file(str(data_path + 'train.txt'),
query_id=True)
    X_test, y_test, qid_test = load_svmlight_file(str(data_path + 'test.txt'),
query_id=True)
    y_train = y_train.astype(int)
    y_test = y_test.astype(int)
    _, group_train = np.unique(qid_train, return_counts=True)
    _, group_test = np.unique(qid_test, return_counts=True)
    return X_train, y_train, qid_train, group_train, X_test, y_test, qid_test,
group_test

def ndcg_single_query(y_score, y_true, k):
    order = np.argsort(y_score)[::-1]
    y_true = np.take(y_true, order[:k])

    gain = 2 ** y_true - 1

    discounts = np.log2(np.arange(len(y_true)) + 2)
    return np.sum(gain / discounts)

# calculate NDCG score given a trained model
def compute_ndcg_all(model, X_test, y_test, qids_test, k=10):
    unique_qids = np.unique(qids_test)
    ndcg_ = list()
    for i, qid in enumerate(unique_qids):
        y = y_test[qids_test == qid]

        if np.sum(y) == 0:
            continue

        p = model.predict(X_test[qids_test == qid])

        idcg = ndcg_single_query(y, y, k=k)
        ndcg_.append(ndcg_single_query(p, y, k=k) / idcg)
    return np.mean(ndcg_)

# get importance of features
```

```
def get_feature_importance(model, importance_type='gain'):
    return model.booster_.feature_importance(importance_type=importance_type)
```

Question 13

```
import os
import zipfile
from sklearn.datasets import load_svmlight_file
import numpy as np
import matplotlib.pyplot as plt

file_path = "MSLR-WEB10K.zip"
destination_path = "MSLR-WEB10K"

# checks if the folder already exists, if not extract
if not os.path.exists(destination_path):
    with zipfile.ZipFile(file_path, 'r') as zip_ref:
        zip_ref.extractall(destination_path)

data_path = "./MSLR-WEB10K/Fold1/"

# loading dataset
X_train, y_train, qid_train = load_svmlight_file(str(data_path + "train.txt"),
query_id=True)

# converting relevance labels to integers
y_train = y_train.astype(int)

num_unique_queries = len(np.unique(qid_train))
print(f"Number of unique queries: {num_unique_queries}")

# computing the distribution of relevance labels
relevance_counts = np.bincount(y_train, minlength=5)
print("Relevance Label Distribution:")
for label, count in enumerate(relevance_counts):
    print(f"Label {label}: {count} occurrences")

# ploting distribution of relevence labels
plt.figure(figsize=(8, 5))
plt.bar(range(5), relevance_counts, tick_label=[0, 1, 2, 3, 4])
plt.xlabel("Relevance Label")
plt.ylabel("Frequency")
plt.title("Distribution of Relevance Labels in Training Data")
plt.show()
```

Output:

Number of unique queries: 6000

Relevance Label Distribution:

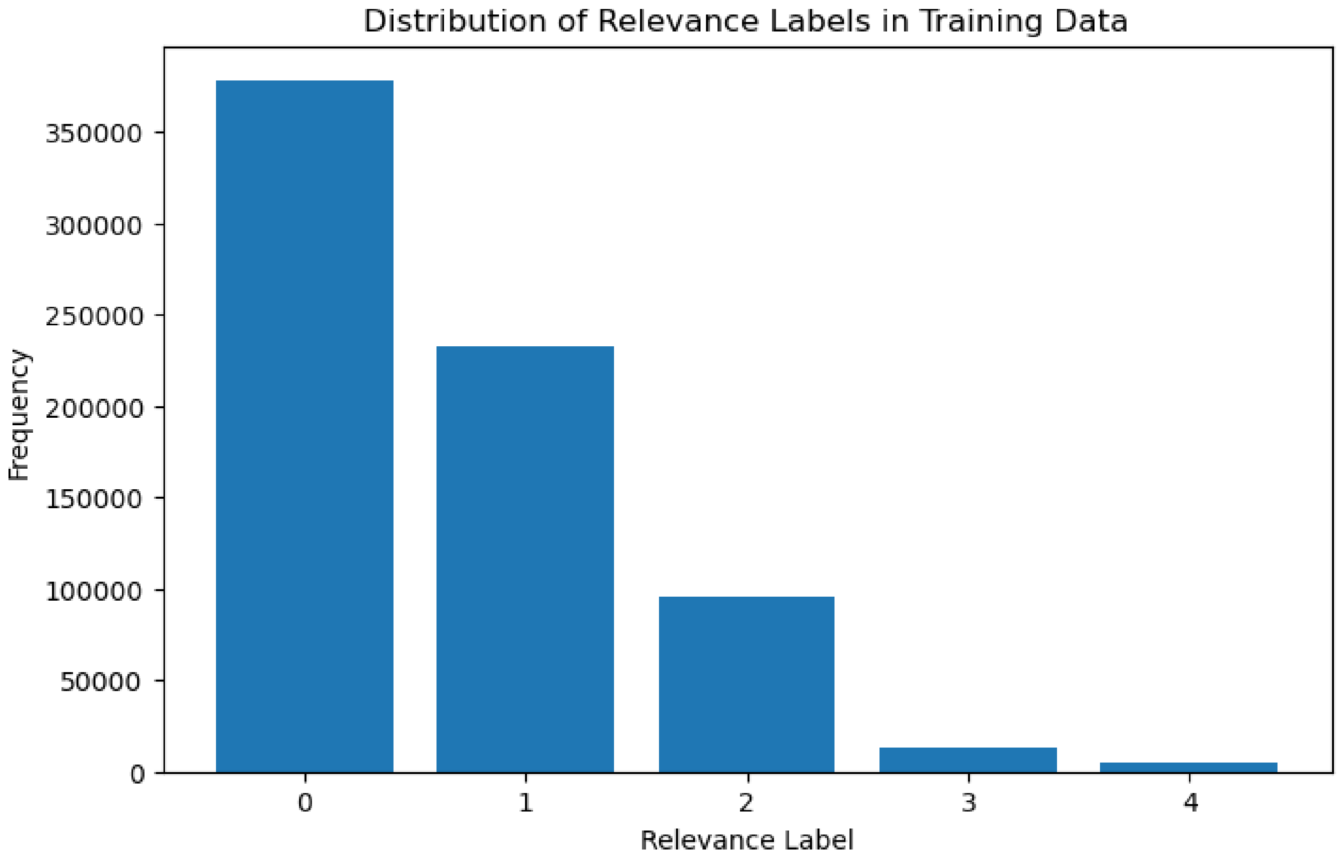
Label 0: 377957 occurrences

Label 1: 232569 occurrences

Label 2: 95082 occurrences

Label 3: 12658 occurrences

Label 4: 5146 occurrences



Question 14

```
import lightgbm as lgb
import pandas as pd
from IPython.display import display

# definitions
dataset_path = "./MSLR-WEB10K/"
folds = [f"Fold{i}" for i in range(1, 6)]
ndcg_k_values = [3, 5, 10]

# Dictionary to store results
results = {}

# Loop through each fold
for fold in folds:
    print(f"\n{fold} Training:\n")
```

```
    # load training and testing data
    data_path = os.path.join(dataset_path, fold)
    X_train, y_train, qid_train = load_svmlight_file(os.path.join(data_path,
"train.txt"), query_id=True)
    X_test, y_test, qid_test = load_svmlight_file(os.path.join(data_path,
"test.txt"), query_id=True)

    # LightGBM dataset format
    train_data = lgb.Dataset(X_train, label=y_train,
group=np.bincount(qid_train.astype(int)))
    test_data = lgb.Dataset(X_test, label=y_test,
group=np.bincount(qid_test.astype(int)), reference=train_data)

    # LightGBM parameters
    params = {
        "objective": "lambdarank",
        "metric": "ndcg",
        "ndcg_eval_at": ndcg_k_values,
        "learning_rate": 0.05,
        "boosting_type": "gbdt",
        "lambda_l1": 0.1,
        "lambda_l2": 0.1,
        "verbosity": -1
    }


    # training LightGBM model
    model = lgb.train(params, train_data, num_boost_round=100, valid_sets=
[test_data])


    # test set score predictions
    y_pred = model.predict(X_test)

    ndcg_scores = {f"nDCG@{k}": ndcg_score([y_test], [y_pred], k=k) for k in
ndcg_k_values}

    results[fold] = ndcg_scores

    # Print nDCG results
    print(f"\n{fold} Performance:")
    for metric, score in ndcg_scores.items():
        print(f"{metric}: {score:.4f}")


results_df = pd.DataFrame(results).T
# Simply print the DataFrame
print("Final nDCG Scores:")
display(results_df)
```

Output:

Fold1 Performance:
nDCG@3: 1.0000
nDCG@5: 1.0000
nDCG@10: 0.9266

Fold2 Performance:
nDCG@3: 1.0000
nDCG@5: 1.0000
nDCG@10: 0.9841

Fold3 Performance:
nDCG@3: 0.8827
nDCG@5: 0.9152
nDCG@10: 0.8936

Fold4 Performance:
nDCG@3: 0.9260
nDCG@5: 0.9465
nDCG@10: 0.9487

Fold5 Performance:
nDCG@3: 0.8520
nDCG@5: 0.8930
nDCG@10: 0.9306
Final nDCG Scores:

Fold	nDCG@3	nDCG@5	nDCG@10
Fold1	1.000000	1.000000	0.926636
Fold2	1.000000	1.000000	0.984095
Fold3	0.882680	0.915210	0.893567
Fold4	0.925980	0.946503	0.948721
Fold5	0.851959	0.893007	0.930569

QUESTION 15: Result Analysis and Interpretation:

For each of the five provided folds, list top 5 most important features of the model based on the importance score. Please use model.booster .feature importance(importance type='gain') as demonstrated here for retrieving importance score per feature. You can also find helper code in the provided notebook.

```
def get_feature_importance(model, importance_type='gain'):
    importance_scores = model.feature_importance(importance_type=importance_type)
    feature_names = model.feature_name()
    importance_dict = {name: score for name, score in zip(feature_names,
importance_scores)}
    return sorted(importance_dict.items(), key=lambda x: x[1], reverse=True)[:5]
```

```python
# Define training parameters
training_params = {
    'objective': 'lambdarank',
    'metric': 'ndcg',
    'learning_rate': 0.1,
    'num_leaves': 31,
    'verbose': -1
}

# Set base directory for data
base_dir = './MSLR-WEB10K/Fold'

# Store feature importances across folds
all_feature_importances = []

# Iterate through each fold (1 to 5)
for fold in range(1, 6):
    fold_data_dir = base_dir + str(fold) + "/"  # Generate fold-specific directory path

    # Load training and test data for this fold
    train_features, train_labels, train_qids, train_groups, test_features, test_labels, test_qids, test_groups = load_one_fole(fold_data_dir)

    # Create dataset objects for training and evaluation
    training_set = lgb.Dataset(train_features, label=train_labels, group=train_groups)
    validation_set = lgb.Dataset(test_features, label=test_labels, group=test_groups, reference=training_set)

    # Train the LightGBM model
    model = lgb.train(training_params, training_set, num_boost_round=100, valid_sets=[validation_set])

    # Extract and display top 5 feature importances
    important_features = get_feature_importance(model, importance_type='gain')
    print(f"Top 5 Features in Fold {fold} (by gain):")
    for feature_name, feature_value in important_features:
        print(f"{feature_name}: {feature_value}")
```

Resulting Output:

Top 5 Features in Fold 1 (by gain): Column_133: 23856.702950954437 Column_7: 4248.546391487122 Column_107: 4135.244449853897 Column_54: 4078.4632263183594 Column_129: 3635.03702378273 Top 5 Features in Fold 2 (by gain): Column_133: 23578.90825009346 Column_7: 5157.964912414551 Column_54: 4386.669756650925 Column_107: 4094.0121722221375 Column_129: 4035.0706725120544 Top 5 Features in Fold 3 (by gain): Column_133: 23218.075441122055 Column_54: 4991.3033719062805 Column_107: 4226.807395458221 Column_129: 4059.7525141239166 Column_7: 3691.792320251465 Top 5 Features in Fold 4 (by gain): Column_133: 23796.899673223495 Column_7: 4622.622978448868 Column_54:

3883.4817056655884 Column_129: 3356.8469800949097 Column_128: 3207.5755367279053 Top 5 Features in Fold 5 (by gain): Column_133: 23540.94235444069 Column_7: 4794.9451723098755 Column_54: 4079.608554124832 Column_107: 3514.8357515335083 Column_129: 3209.0584440231323

QUESTION 16: Experiments with Subset of Features:

For each of the five provided folds:

- Remove the top 20 most important features according to the computed importance score in the question 15. Then train a new LightGBM model on the resulted 116 dimensional query- url data. Evaluate the performance of this new model on the test set using nDCG. Does the outcome align with your expectations? If not, please share your hypothesis regarding the potential reasons for this discrepancy.
- Remove the 60 least important features according to the computed importance score in the question 15. Then train a new LightGBM model on the resulted 76 dimensional query-url data. Evaluate the performance of this new model on the test set using nDCG. Does the outcome align with your expectations? If not, please share your hypothesis regarding the potential reasons for this discrepancy.

```
# Load the dataset for one fold
def load_one_fole(data_path):
    X_train, y_train, qid_train = load_svmlight_file(str(data_path + 'train.txt'),
query_id=True)
    X_test, y_test, qid_test = load_svmlight_file(str(data_path + 'test.txt'),
query_id=True)
    y_train = y_train.astype(int)
    y_test = y_test.astype(int)
    _, group_train = np.unique(qid_train, return_counts=True)
    _, group_test = np.unique(qid_test, return_counts=True)
    return X_train, y_train, qid_train, group_train, X_test, y_test, qid_test,
group_test

def ndcg_single_query(y_score, y_true, k):
    order = np.argsort(y_score)[::-1]
    y_true = np.take(y_true, order[:k])

    gain = 2 ** y_true - 1

    discounts = np.log2(np.arange(len(y_true)) + 2)
    return np.sum(gain / discounts)

# calculate NDCG score given a trained model
def compute_ndcg_all(model, X_test, y_test, qids_test, k=10):
    unique_qids = np.unique(qids_test)
    ndcg_ = list()
    for i, qid in enumerate(unique_qids):
        y = y_test[qids_test == qid]

        if np.sum(y) == 0:
            continue
```

```
        p = model.predict(X_test[qids_test == qid])

        idcg = ndcg_single_query(y, y, k=k)
        ndcg_.append(ndcg_single_query(p, y, k=k) / idcg)
    return np.mean(ndcg_)

def get_important_features_indices(model, num_features, least_important=False):
    # Extract feature importances based on gain
    feature_importances = model.feature_importance(importance_type='gain')

    # Determine whether to return least or most important features
    sorted_indices = np.argsort(feature_importances)
    return sorted_indices[:num_features] if least_important else sorted_indices[-
num_features:]
```

```
# Define LightGBM parameters
params = {
    'objective': 'lambdarank',
    'metric': 'ndcg',
    'learning_rate': 0.1,
    'num_leaves': 31,
    'verbose': -1
}

# Base path for dataset folds
base_data_path = './MSLR-WEB10K/Fold'

# Iterate through each fold
for fold_idx in range(1, 6):
    data_path = base_data_path + str(fold_idx) + "/"  # Generate the fold-specific
path
    X_train, y_train, qid_train, group_train, X_test, y_test, qid_test, group_test
= load_one_fole(data_path)

    # Prepare LightGBM datasets
    train_data = lgb.Dataset(X_train, label=y_train, group=group_train)
    test_data = lgb.Dataset(X_test, label=y_test, group=group_test,
reference=train_data)

    # Train the initial model
    model = lgb.train(params, train_data, num_boost_round=100, valid_sets=
[test_data])

    # Identify and remove the top 20 most important features
    top_features_indices = get_important_features_indices(model, 20)
    X_train_reduced_top, X_test_reduced_top = X_train[:, top_features_indices],
X_test[:, top_features_indices]
    train_data_reduced_top = lgb.Dataset(X_train_reduced_top, label=y_train,
group=group_train)
    test_data_reduced_top = lgb.Dataset(X_test_reduced_top, label=y_test,
```

```
group=group_test)

    # Retrain with top features removed
    model_reduced_top = lgb.train(params, train_data_reduced_top,
num_boost_round=100, valid_sets=[test_data_reduced_top])
    ndcg_score_reduced_top = compute_ndcg_all(model_reduced_top,
X_test_reduced_top, y_test, qid_test)
    print("Fold {}, Top 20 Features Removed, NDCG Score: {}".format(fold_idx,
ndcg_score_reduced_top))

    # Identify and remove the bottom 60 least important features
    bottom_features_indices = get_important_features_indices(model, 60,
least_important=True)
    X_train_reduced_bottom, X_test_reduced_bottom = X_train[:,
bottom_features_indices], X_test[:, bottom_features_indices]
    train_data_reduced_bottom = lgb.Dataset(X_train_reduced_bottom, label=y_train,
group=group_train)
    test_data_reduced_bottom = lgb.Dataset(X_test_reduced_bottom, label=y_test,
group=group_test)

    # Retrain with bottom features removed
    model_reduced_bottom = lgb.train(params, train_data_reduced_bottom,
num_boost_round=100, valid_sets=[test_data_reduced_bottom])
    ndcg_score_reduced_bottom = compute_ndcg_all(model_reduced_bottom,
X_test_reduced_bottom, y_test, qid_test)
    print("Fold {}, Bottom 60 Features Removed, NDCG Score: {}".format(fold_idx,
ndcg_score_reduced_bottom))
```

Resulting Output:

Fold 1, Top 20 Features Removed, NDCG Score: 0.47827689648179766 Fold 1, Bottom 60 Features Removed, NDCG Score: 0.3725346737876415 Fold 2, Top 20 Features Removed, NDCG Score: 0.4738541279047724 Fold 2, Bottom 60 Features Removed, NDCG Score: 0.35378669585571704 Fold 3, Top 20 Features Removed, NDCG Score: 0.47214671154446586 Fold 3, Bottom 60 Features Removed, NDCG Score: 0.367133083900162 Fold 4, Top 20 Features Removed, NDCG Score: 0.4800954917400635 Fold 4, Bottom 60 Features Removed, NDCG Score: 0.37409776466008327 Fold 5, Top 20 Features Removed, NDCG Score: 0.4839351910646641 Fold 5, Bottom 60 Features Removed, NDCG Score: 0.35427364869638417

Answer to questions:

As we can see, removing the top 20 most important features significantly dropped nDCG scores from around 0.85-1.0 to 0.47-0.48. This is expected since these features had the highest predictive power. Also, when we remove the 60 least important features, it lowered scores even more to 0.35-0.37, which shows that these features still contributed useful ranking signals. This suggests that feature interactions and regularization effects did play a role where unimportant features improved performance. This also might mean that low importance features might not be useful alone, but together they could contribute meaningfully to the model when combined with other features. Overall, the results show that removing high importance features weakens the model, but blindly eliminating low importance ones can also be harmful because of the loss of weak but still useful signals.