Project Report

**Covid-19 Predictive modeling dashboard**

**1. Problem Statement:**

Coronavirus disease (COVID-19) is an infectious disease caused by the SARS-CoV-2 virus. The first known infections from SARS-CoV-2 were discovered in Wuhan, China. Since then, the virus has spread over multiple companies and evolved into a pandemic. The economic and social disruption caused by the pandemic is devastating. Millions of enterprises face an existential threat. Nearly half of the world’s 3.3 billion global workforce are at risk of losing their livelihoods.

Travel and tours industry is one of the worst hit industries that had a major revenue fall after the outbreak of Covid 19 pandemic. Having a system that can monitor the current situation of Covid around the world provides better control and improve confidence at a time of uncertainty. We are interested in developing the following:

* An ELT pipeline to fetch daily covid data into data lake and perform necessary transformations on the data
* A machine learning model that can make projections on the anticipated number of covid cases for the upcoming 3-month period based on past data and current trends.
* Dashboard with different visualizations for analysing the covid related data and projections on number of active cases, hospitalizations, recovery rate and deaths.

**2. Data**

* [COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University](https://github.com/CSSEGISandData/COVID-19) This is the data repository for the 2019 Novel Coronavirus Visual Dashboard operated by the Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE). Also, Supported by ESRI Living Atlas Team and the Johns Hopkins University Applied Physics Lab (JHU APL).
* [Canada population by province](https://www.statista.com/statistics/481509/canada-population-projection-by-province/) This dataset contains the population data of various provinces in Canada

## 3. Method

## 3.1 Data Ingestion using pipelines

Covid – 19 data on number of confirmed cases, hospital admissions, deaths etc. are constantly changing. The primary dataset used here is the GitHub Data Repository by the Center for Systems Science and Engineering of CSSE at Johns Hopkins University.

To make up-to-date predictions and live dashboard, our dataset must update at regular intervals. To achieve this, we are creating ELT pipelines using Azure Data Factory. Azure blob storage is used for storing population data. A pipeline is created for ingesting this data into Azure Data Lake Gen 2. The architecture is shown below.

A picture containing graphical user interface

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Diagram

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Another pipeline is created for ingesting daily covid data. The pipeline is scheduled to run every day at a specific time using triggers. The architecture is shown below.

Graphical user interface, application

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The final data is available in the data warehouse. The Tableau and Power BI dashboard, and ML models fetch the data from this dashboard.

## 3.1 Data Wrangling

[Data Wrangling Report](https://github.com/VargheseTresa/projects/blob/main/Covid%20EDA%20and%20forecasting/project/notebooks/01_data_wrangling.ipynb)

The original dataset includes confirmed cases and deaths data from all over the world since Jan 22, 2020, to the current date. We are specifically interested in only data pertaining to different provinces in Canada. Hence, we first filter out all other data.

**Handling of missing values:**

Null values are present only for Repatriated Travellers. This row will eventually get eliminated when we filter for top 10 provinces based on number of deaths. So no treatment of null values needed.

**Preprocessing and feature engineering:**

For each province, a separate data frame is created. In each province data frame, we convert it into a time series data by using pivot operation. We begin by melting wide data frame is into long data frame. Then the following features are extracted.

* The cases and deaths reported are running totals. From this data, number of daily deaths and confirmed cases are extracted.
* To assist with further analysis, the 7 day and 30-day moving average of confirmed cases and deaths are calculated
* To filter out noise and to identify trends, exponential weighted moving average is calculated for confirmed cases and deaths.
* Mortality rate is calculated as ratio of number of deaths to number of confirmed cases
* Few errors in number of cases and deaths reported (present day number lower than previous day number) led to negative values for number of new cases. These are replaced with zero as number of new cases/deaths for that day.
* The time series data created is written as csv file for further EDA and creation of dashboard in Tableau.

## 3.2 EDA

[Tableau Dashboard](https://public.tableau.com/app/profile/tresa6898/viz/CovidDashboardCanada/Trends-Deaths)

**Trends in number of cases and deaths:**

First, overall trend in number of confirmed cases and deaths since the beginning of reporting are plotted. To get better insights, along with daily new cases, 7-day moving average and 30-day moving average values were also calculated and plotted.

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Chart, line chart

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The period in December sees an exponential growth in number of confirmed cases; however, number of deaths doesn’t seem to grow in a similar rate. To confirm that, lets further dig deep into period starting from October 2021. This time, we have a look at number of daily new confirmed cases and deaths, 7-day moving average and exponential weighted moving average.

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Chart, histogram

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Chart, bar chart

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Chart, bar chart

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Approximately 70% of the customers who left the company had Fibre Optic Internet service. This along with above data collected from customers who left the company indicates that better internet service from competitor could be a significant factor leading to customer churn.

### **Statistical estimation of average churn score of customers who churn**

To determine how useful is the feature churn score in predicting the probability of customer churn, we look at the distribution of churn score and mean churn score for customers who churn and who do not churn.

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It is evident that customers who churn have higher churn score. Bootstrapping technique is applied to statistically estimate the confidence interval for the difference in mean churn score for customers who churn and customers who do not churn. The 95% confidence interval of the difference between mean churn scores of customers from both categories is estimated to be between 31.74 and 33.01.

### **Correlation Analysis**

Graphical user interface, chart, table

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There is strong correlation between columns related to geography such as Zip Code, Latitude and Longitude. Also, target variable Churn Value is **negatively correlated** with Tenure months and **positively correlated** with Churn Score.

## 3.3 Predictive Modeling

[ML Notebook](https://github.com/VargheseTresa/SpringBoard/blob/main/CAP2/CAP2_modelling.ipynb)

**Overview**:

To predict whether a customer will churn given various attributes of the customer, we build a machine learning model. We split the available data into train (80% of data) and test sets (remaining 20% of data). We train different machine learning algorithms using the training set. Also perform hyperparameter tuning of the models using cross validation. Then compare the results to find the best model that suits our problem context. I have selected 3 machine learning algorithms for my initial review.

#### **1 . Ada Boost**

An AdaBoost classifier is a meta-estimator that begins by fitting a classifier on the original dataset and then fits additional copies of the classifier on the same dataset but where the weights of incorrectly classified instances are adjusted such that subsequent classifiers focus more on difficult cases.

#### **2. Linear Discriminant Analysis**

A classifier with a linear decision boundary, generated by fitting class conditional densities to the data and using Bayes’ rule. The model fits a Gaussian density to each class, assuming that all classes share the same covariance matrix.

#### **3. Light Gradient Boosting Machine**

LightGBM, short for Light Gradient Boosting Machine, is a free and open source distributed gradient boosting framework for machine learning originally developed by Microsoft. It is based on decision tree algorithms and used for ranking, classification and other machine learning tasks.

**Model Evaluation:**

Here, accurately predicting churn = 1 is critical. If a customer is mis predicted as churn = 0, the company fails to apply necessary retention measures to retain that customer and thereby increases the chances of the customer leaving the country. Hence, our aim is to reduce the False Negatives and increase the True Positives. Thus, we give more importance to the Recall score and rank the models based on best Recall score.

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Best Recall score (Class: 1) = 0.845

Model : Linear Discriminant Analysis

From the confusion matrix, it is evident that Linear Discriminant Analysis achieves the best recall score and minimum False Negative number. Hence we choose this model for our final prediction.

The contribution of different features in the prediction is identified as shown below.

Graphical user interface, application, table

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Churn Score is a major contributor in predicting whether customer will churn. Tenure Months and Monthly Charges are few other important features identified as significant to prediction process.

The boundary plot of the data is shown below.

Chart, scatter chart

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**4. Takeaways**

* EDA revealed that customers who are on month-to-month contract have high probability to churn compared to those on 2-year contract.
* Churn Score is a good predictor of customer churn. The difference between average churn score of those who churn and do not churn is between 31.74 and 33.01.
* Among the customers who churned, 70% of them had Fibre Optic Internet Service with the company. Analysis of churn reason also reveals that 33% of the customers who left the company were offered with better internet or devices by competitors.
* Among the customers who left the company, 37% were not satisfied with the services provided by the company.

**5. Future Extensions**

Availability of transaction data of customers can further assist in finding time sensitive trends in customer behavior.

More research on competitors in the market and the services they offer can reveal any attention needed on the services and packages offered by the company. It also helps in understanding where the company stands in the competitive market.

**6. References**

Not all the work in this notebook is original. Some parts were borrowed from online resources. I take no credit for parts that are not mine. They were solely used for illustration purposes.

1. https://www.statisticshowto.com/welchs-test-for-unequal-variances/

2. https://medium.com/@sosterburg/mapping-data-with-folium-356f0d6f88a9