Advanced Data Science withIBM Specialization

Stakeholder Presentation

- Problem Statement
- Dataset
- Use cases
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Predict average spend on Food & Beverages by a holiday resort member

Problem Statement

The company, the most preferred holiday resort chain in India makes significant revenue from Food and Beverages (F&B) sales in their resorts. The members of the company club are offered a wide variety of items in either buffet or restaurant form.

Given the information related to resort, club member, reservation etc. the task is to predict average spend per room night on food and beverages for each reservation.

This is a regression problem, and we will train a machine learning model on the provided data to give the predictions.

The Dataset

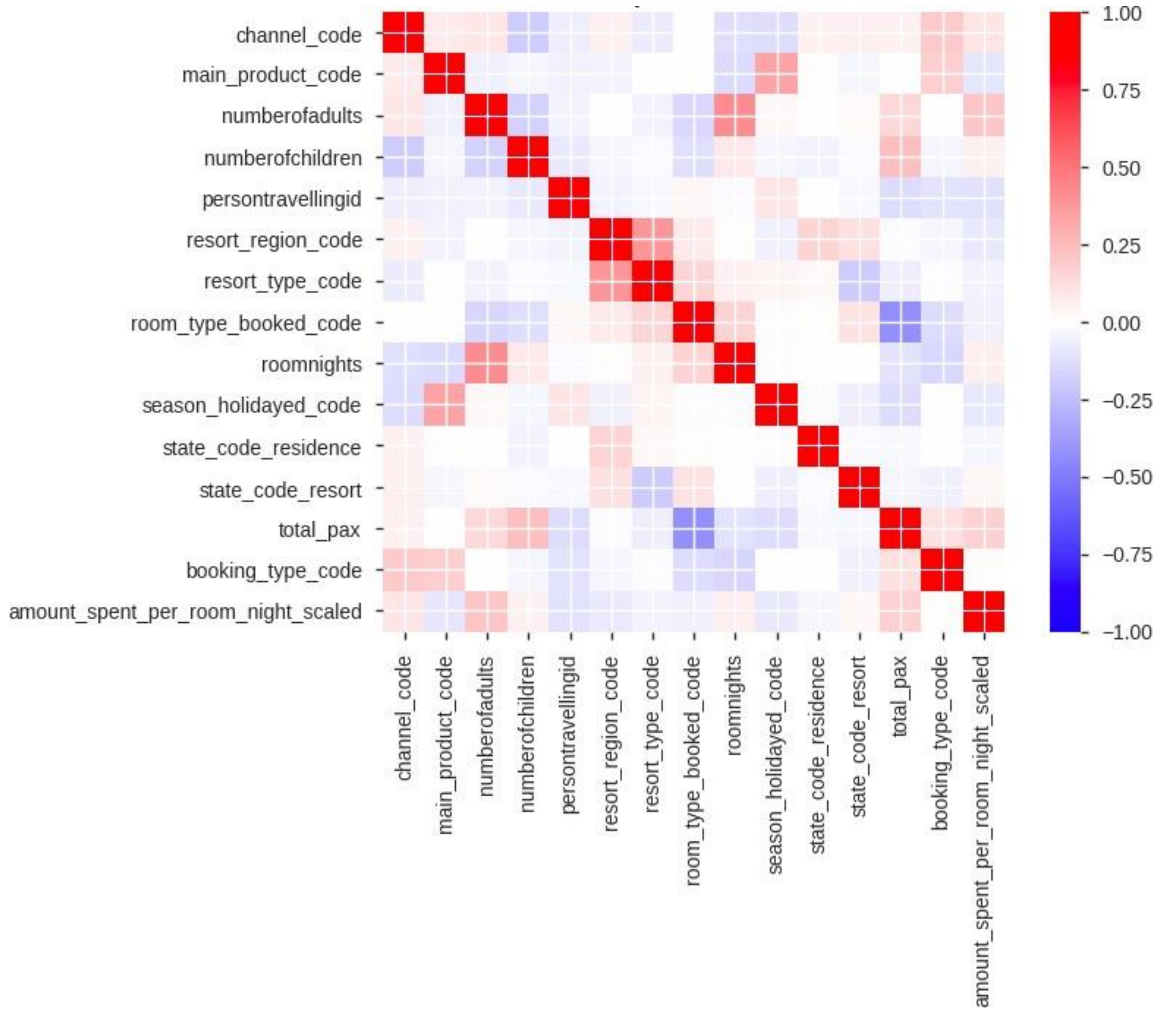
Dataset info

Number of variables	24
Number of observations	314 424
Total Missing (%)	0.1%

Variables types

Numeric	11
Categorical	14
Date	3

Correlation Matrix



The variables have been anonymized:

- Categories (resort, state etc.) replaced with codes.
- Target variable (amount spent per room night) scaled.

The variables most correlated with the target:

- `total_pax` – total number of persons travelling
- `numberofadults` – number of adults travelling
- `roomnights` – number of room nights booked
- `channel_code` – different channels for booking
- `state_code_resort` – state in which resort is located

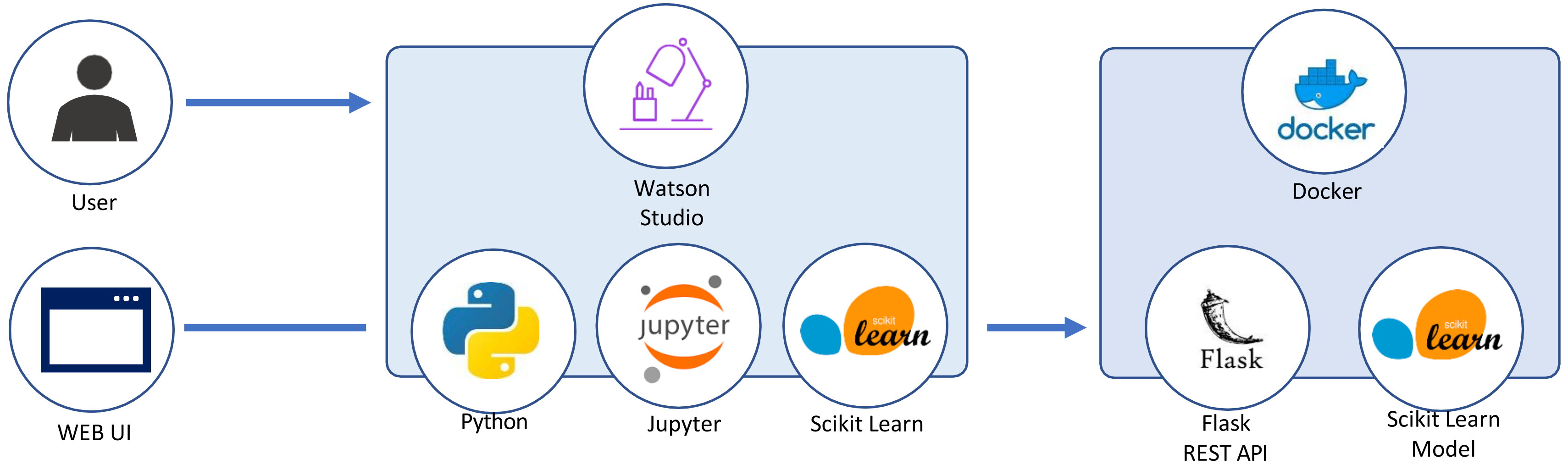
The Use Case and the Solution

Following are some benefits the prediction model will bring:

- Predicting the F&B spend of a member in a resort would help in improving the pre-sales during resort booking through web and mobile app.
- Targeted campaigns to suit the member taste and preference of F&B.
- Providing members in the resort with a customized experience and offers.
- Help resort kitchen to plan the inventory and food quantity to be prepared in advance.

The data preparation and model training is conducted with Watson Studio. It uses Python, scikit learn and Jupyter technology. And deployed as a web-service with IBM Cloud.

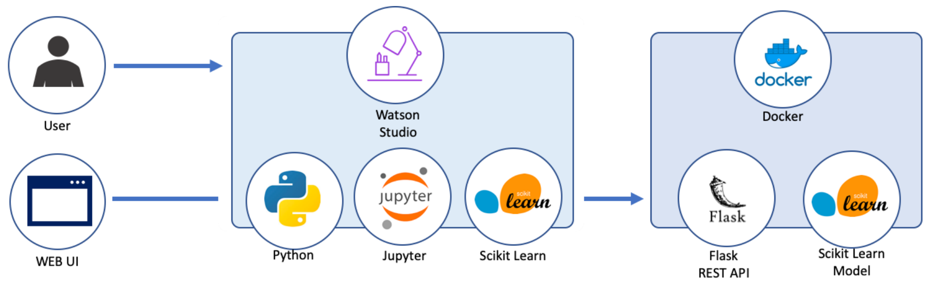
The solution architecture:



Technical Presentation

- Architectural choices
- Data quality assessment, data pre-processing and feature engineering
- Model performance indicators
- Model algorithm

Architectural Choices



Core solution:
User provided CSV file uploaded to Watson Studio / IBM Object Storage.

Scikit-learn and Python in IBM Watson Studio with Jupyter notebooks:
- ETL; Data Exploration.
- Feature Engineering; Model Definition and Validation.
- Pipeline Notebook (takes raw CSV data and outputs the trained pipeline ready for deployment).

Trained model is saved and deployed as Flask REST API with Dash UI hosted at IBM Cloud.

Alternative solution:
- IBM Watson Studio Data refinery flow for raw data preparation.
- Watson Machine Learning automatic modeling deployed as REST API web-service.

Data Pre-Processing and Feature Engineering

EDA

- 24 variables and 314 424 observations (unique reservations).
- 0.1% of total values are missing, 1.4% of missing values in `resort_type_code`.
- `booking_date`, `checkin_date` and `checkout_date` are date variables and should be parsed to datetime format at data loading stage.
- `memberid` has high cardinality: 101 327 unique values.
- `numberofchildren` has 77.4% of zero values.

Feature Engineering

- **Date features**: `booking_in_advance`, `days_stayed`
- Other features containing the information from the date (`month`, `week`, `dayofweek`, `is_month_start` etc.)
- **Other features** (`n_people` etc.)

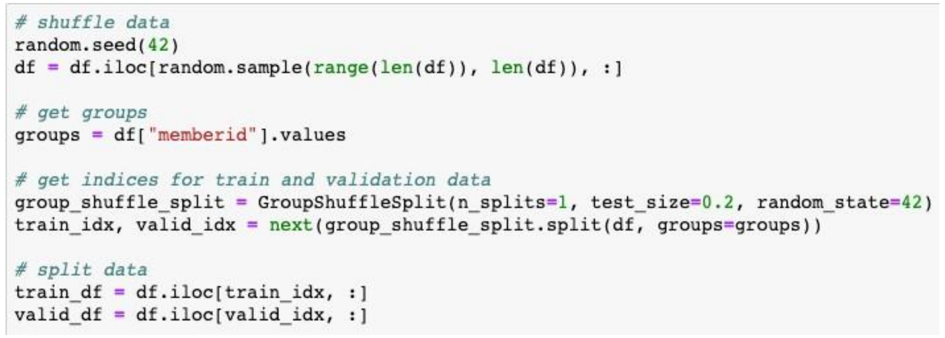
Pre-processing

- Fill NA values with -1
- Convert binary-type columns values to [0, 1]
- OHE for categorical features
- Scale the numerical features

Model Performance Indicators

The model is evaluated on Root-Mean-Squared-Error (RMSE) between the predicted value and the observed amount spent.

The train/valid split performed based on `memberid` variable to prevent the data leak: we want to be able to predict the amount spent for the new members of hotels.

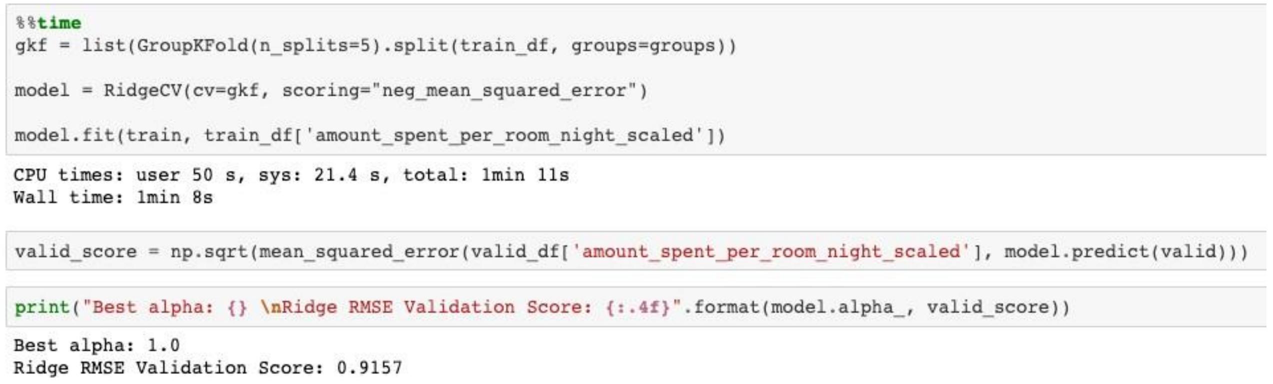


```
# shuffle data
random.seed(42)
df = df.iloc[random.sample(range(len(df)), len(df)), :]

# get groups
groups = df["memberid"].values

# get indices for train and validation data
group_shuffle_split = GroupShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
train_idx, valid_idx = next(group_shuffle_split.split(df, groups=groups))

# split data
train_df = df.iloc[train_idx, :]
valid_df = df.iloc[valid_idx, :]
```

Model Algorithm

The chosen model is **Linear Regression** with L2 regularization (Ridge Regression).

Model parameters are tuned on 5-fold cross validation stratified by `memberid` groups.
The model performance is than validated with unseen data:



```
%%time
gkf = list(GroupKFold(n_splits=5).split(train_df, groups=groups))

model = RidgeCV(cv=gkf, scoring="neg_mean_squared_error")

model.fit(train, train_df['amount_spent_per_room_night_scaled'])
```

```
CPU times: user 50 s, sys: 21.4 s, total: 1min 11s
Wall time: 1min 8s
```

```
valid_score = np.sqrt(mean_squared_error(valid_df['amount_spent_per_room_night_scaled'], model.predict(valid)))
```

```
print("Best alpha: {} \nRidge RMSE Validation Score: {:.4f}".format(model.alpha_, valid_score))
```

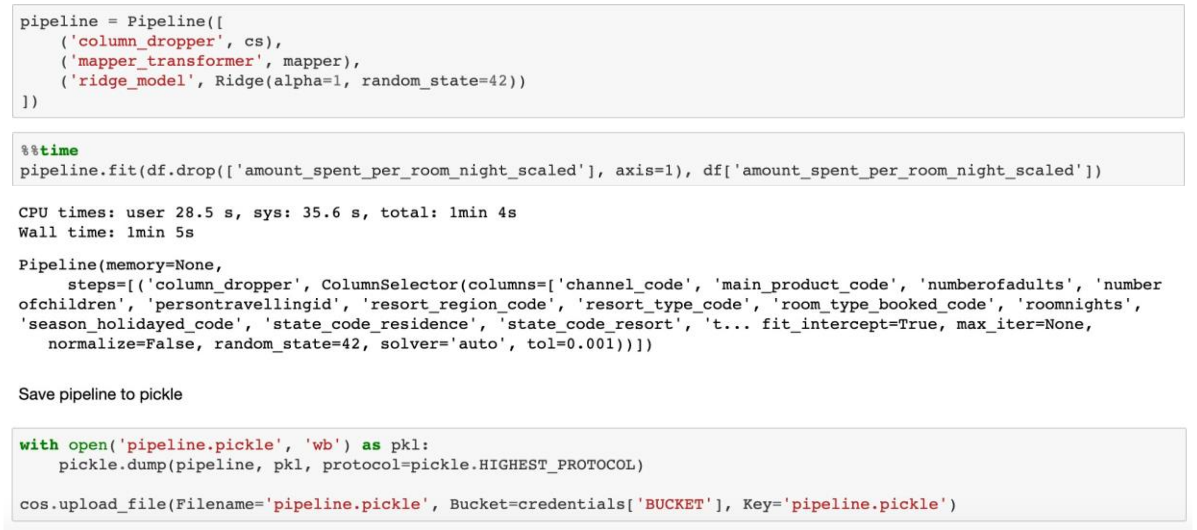
```
Best alpha: 1.0
Ridge RMSE Validation Score: 0.9157
```

The model is trained and cross-validated in under 2 minutes with Watson Studio Lite plan (1 vCPU and 4 Gb RAM) and shows **RMSE score of 0.9157.**

Model Deployment

After model training and evaluation, we create separate Jupyter notebook with full pipeline:

1. Loading data.
2. Pre-processing.
3. Create and save sklearn pipeline object to pickle file:
   - Choose columns
   - Transform columns
   - Train the model



```
pipeline = Pipeline([
    ('column_dropper', cs),
    ('mapper_transformer', mapper),
    ('ridge_model', Ridge(alpha=1, random_state=42))
])
```

```
%%time
pipeline.fit(df.drop(['amount_spent_per_room_night_scaled'], axis=1), df['amount_spent_per_room_night_scaled'])
```

```
CPU times: user 28.5 s, sys: 35.6 s, total: 1min 4s
Wall time: 1min 5s

Pipeline(memory=None,
     steps=[('column_dropper', ColumnSelector(columns=['channel_code', 'main_product_code', 'numberofadults', 'number
ofchildren', 'persontravellingid', 'resort_region_code', 'resort_type_code', 'room_type_booked_code', 'roomnights',
'season_holidayed_code', 'state_code_residence', 'state_code_resort', 't... fit_intercept=True, max_iter=None,
   normalize=False, random_state=42, solver='auto', tol=0.001))])
```

Save pipeline to pickle

```
with open('pipeline.pickle', 'wb') as pkl:
    pickle.dump(pipeline, pkl, protocol=pickle.HIGHEST_PROTOCOL)

cos.upload_file(Filename='pipeline.pickle', Bucket=credentials['BUCKET'], Key='pipeline.pickle')
```

The fitted and trained pipeline is then deployed as Flask REST API service with minimalist web-interface created with Dash, running at IBM Cloud.