**目** 댓글 ♣ 공유 🌣

📤 kickstarter database.ipynb 🔯

# KeyboardInterrupt: SEARCH STACK OVERFLOW [ ] kick\_df.dtypes [ ] # Configure settings for RDS mode = "append" jdbc\_url="jdbc:postgresql://kickstarter.c90yn2pvfvlh.us-east-2.rds.amazonaws.com:5432/postgres" config = {"user":"postgres", "password": "Laurent123!", "driver": "org.postgresql.Driver"} [ ] # Write DataFrame to mask table in RDS kick\_df.write.jdbc(url=jdbc\_url, table='kickstarter', mode=mode, properties=config) [ ] # Import our dependencies from sklearn.model\_selection import train\_test\_split from sklearn.preprocessing import StandardScaler from sklearn.ensemble import RandomForestClassifier from sklearn.metrics import accuracy score from sklearn.preprocessing import OneHotEncoder import pandas as pd import tensorflow as tf import numpy as np

# kick\_df = kick\_df.select("\*").toPandas()

Preprocessing for machine learning

[ ] # Change the PySpark dataframes into Pandas dataframes

We will inspect the data to see if there's any categorical variable or NA values that we need to drop.

```
# Generate our categorical variable list
df_cat = df.dtypes[df.dtypes == "object"].index.tolist()

[ ] kick_df_cat = kick_df.dtypes[kick_df.dtypes == "object"].index.tolist()
```

▼ I. Inspect whether we need bucketing of variables in categorical columns

```
df[df_cat].nunique()
[ ] kick_df[kick_df_cat].nunique()
```

## II. Encode the categorical variables

First, we will inspect each column on NA values and whether we need to bucket any of the values together in each categorical column. Bucketing them if needed

```
# Print out each Category value counts of a categorical column
cate_counts = df.ColumnName.value_counts()

# Visualize the value counts
cate_counts.plot.density()

# Determine which values to replace
replace = list(cate_counts[cate_counts < #].index)

# Replace in DataFrame
for value in replace:
    df.ColumnName = df.ColumnName.replace(value, "Bucket")

# Check to make sure binning was successful
df.ColumnName.value_counts()</pre>
```

Then, move onto encoding the categorical columns. OR just skip to this part if bucketing is unnessary.

```
# Create a OneHotEncoder instance
from sklearn.preprocessing import OneHotEncoder
enc = OneHotEncoder(sparse=False)

# Fit and transform the OneHotEncoder using the categorical variable list
encode_df = pd.DataFrame(enc.fit_transform(df_ColumnName.values.resape(-1,1)))

# Add the encoded variable names to the DataFrame
encode_df.columns = enc.get_feature_names(['ColumnName'])
```

```
encode_df.head()
```

Finally, merge the encoded DataFrame with the original df and drop the original columns.

```
df.merge(encode_df, left_index=True, right_index=True).drop("ColumnName", 1)
```

## III. Decide on columns to drop

Inspect null values in each column and decide whether it's worth to drop or fill NA with 0s if needed. Then, we will drop columns that are not adding valuable information such as "name" and id" columns in the kick\_df.

#### IV. Trial and Error for Machine Learning models: Random Forests versus Neural Networks

Since we will be developing a model that can identify whether a project will success with the funding, we will be using a binary classification.

To get started we will define features and the output.

```
# Split our preprocessed data into our features and target arrays
y = new_df["OutputColumn"].values
X = new_df.drop(["OutputColumn"],1).values

For our dataset, the output column will be "state" column.
# Split the data into testing and training dataset before standardizing the data.
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=78)
```

#### VI. Standardize the data

```
# Create a StandardScaler instance
scaler = StandardScaler()

# Fit the StandardScaler
X_scaler = scaler.fit(X_train)

# Scale the data
X_train_scaled = X_scaler.transform(X_train)
X_test_scaled = X_scaler.transform(X_test)
```

#### VII. Random Forests

```
# Create a random forest classifier.
rf_model = RandomForestClassifier(n_estimators=128, random_state=78)

# Fitting the model
rf_model = rf_model.fit(X_train_scaled, y_train)

# Evaluate the model
y_pred = rf_model.predict(X_test_scaled)
print(f" Random forest predictive accuracy: {accuracy_score(y_test,y_pred):.3f}")
```

# VIII. Support Vector Machine

```
# Create the SVM model
svm = SVC(kernel='sigmoid')
# Train the model
svm.fit(X_train, y_train)
# Evaluate the model
y_pred= svm.predict(X_test_scaled)
print(f" SVM model accuracy: {accuracy_score(y_test,y_pred):.3f}")
```

# IX. Neural Networks

```
# Define the model - deep neural net
number_input_features = len(X_train[0])
hidden_nodes_layer1 = 8 # number of neurons will change depending on the nature of the dataset (2-3 times the number of
hidden_nodes_layer2 = 5
nn = tf.keras.models.Sequential()
# First hidden layer
nn.add(
```

```
# Second hidden layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer2, activation="relu"))
# Output layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer2, activation="relu"))
# Check the structure of the model
nn.summary()
# Compile the model
nn.compile(loss="binary_crossentropy", optimizer="adam", metrics=["accuracy"])
# Train the model
fit_model = nn.fit(X_train,y_train,epochs=100)
# Evaluate the model using the test data
model_loss, model_accuracy = nn.evaluate(X_test,y_test,verbose=2)
print(f"Loss: {model_loss}, Accuracy: {model_accuracy}")
```

```
[ ] # Creating a dataframe grouped by category with columns for failed and successful
    cat_df = pd.get_dummies(df.set_index('category').state).groupby('category').sum()
    fig, ((ax1, ax2), (ax3, ax4), (ax5, ax6)) = plt.subplots(3, 2, figsize=(12,12))
    color = cm.CMRmap(np.linspace(0.1,0.8,df.category.nunique())) # Setting a colormap
    df.groupby('category').category.count().plot(kind='bar', ax=ax1, color=color)
    ax1.set_title('Number of projects')
    ax1.set_xlabel('')
    df.groupby('category').usd_goal.median().plot(kind='bar', ax=ax2, color=color)
    ax2.set_title('Median project goal ($)')
    ax2.set_xlabel('')
    df.groupby('category').usd_pledged.median().plot(kind='bar', ax=ax3, color=color)
    ax3.set_title('Median pledged per project ($)')
    ax3.set_xlabel('')
    cat_df.div(cat_df.sum(axis=1), axis=0).successful.plot(kind='bar', ax=ax4, color=color) # Normalizes counts across rows
    ax4.set_title('Proportion of successful projects')
    ax4.set_xlabel('')
    df.groupby('category').backers_count.median().plot(kind='bar', ax=ax5, color=color)
    ax5.set_title('Median backers per project')
    ax5.set_xlabel('')
    df.groupby('category').pledge_per_backer.median().plot(kind='bar', ax=ax6, color=color)
    ax6.set_title('Median pledged per backer ($)')
    ax6.set xlabel('')
    fig.subplots_adjust(hspace=0.6)
    plt.show()
```