ITCS 6100
Big Data Analytics for Competitive Advantages
Group 15
canvas-sample-datasets

Team Members

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Dataset

For understanding and exploration of the loan repayment status we have chosen this dataset. The dataset consists of 21 column and around 40000 rows.
S3 PATH s3://projectbucket15/canvas-loan-dataset.csv

AWS Services Used

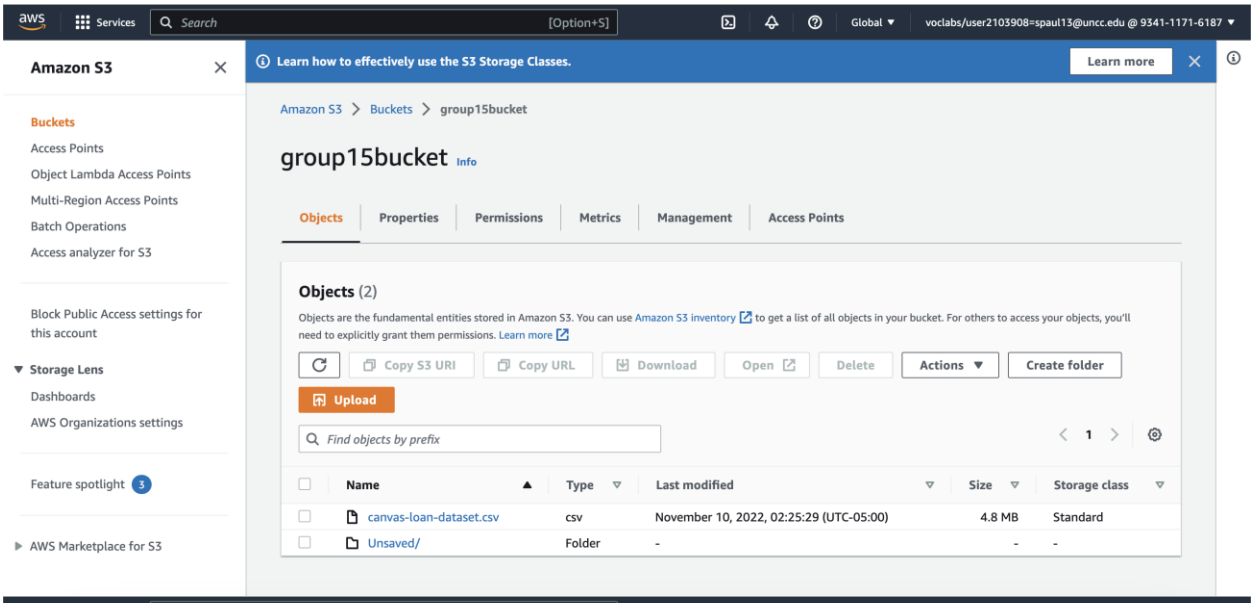
1. AWS S3
2. AWS Glue
3. AWS Athena
4. AWS QuickSight
5. AWS SageMaker

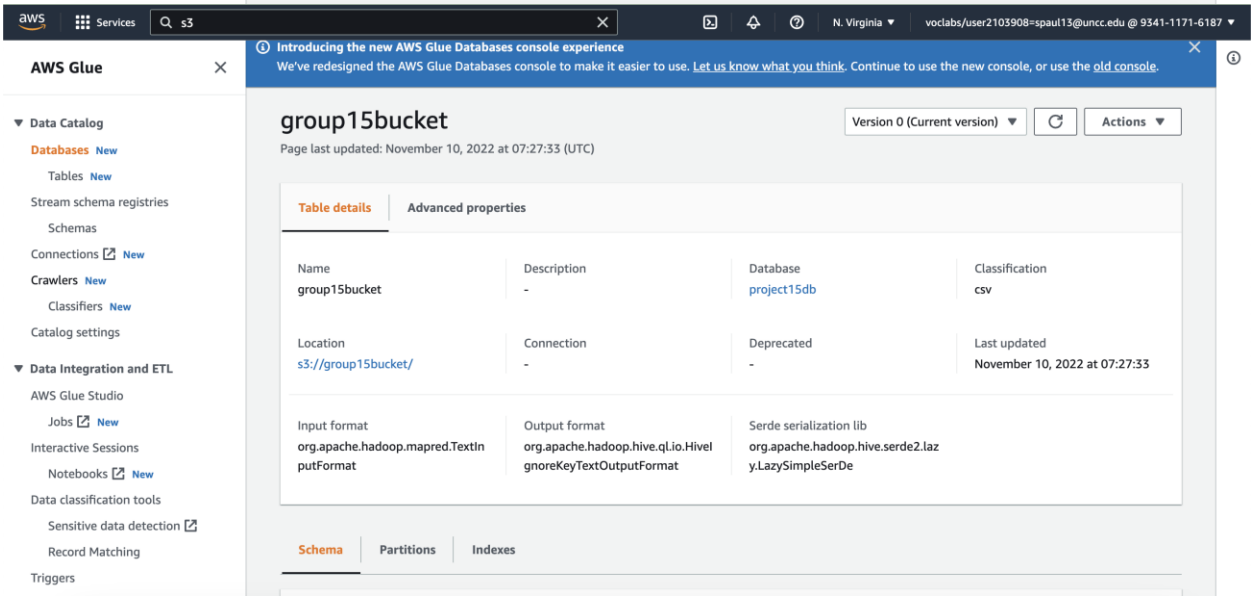
About Data

Research objective is to predict, whether a customer will repay a loan or not. The dataset contains complete loan data for all loans issued from 2007-20011 including the current loan status and latest payment information. Target column for this dataset is loan_status. The dataset consists of ~40000 rows, 21 features columns.

Creation of Bucket and storing the dataset into the bucket

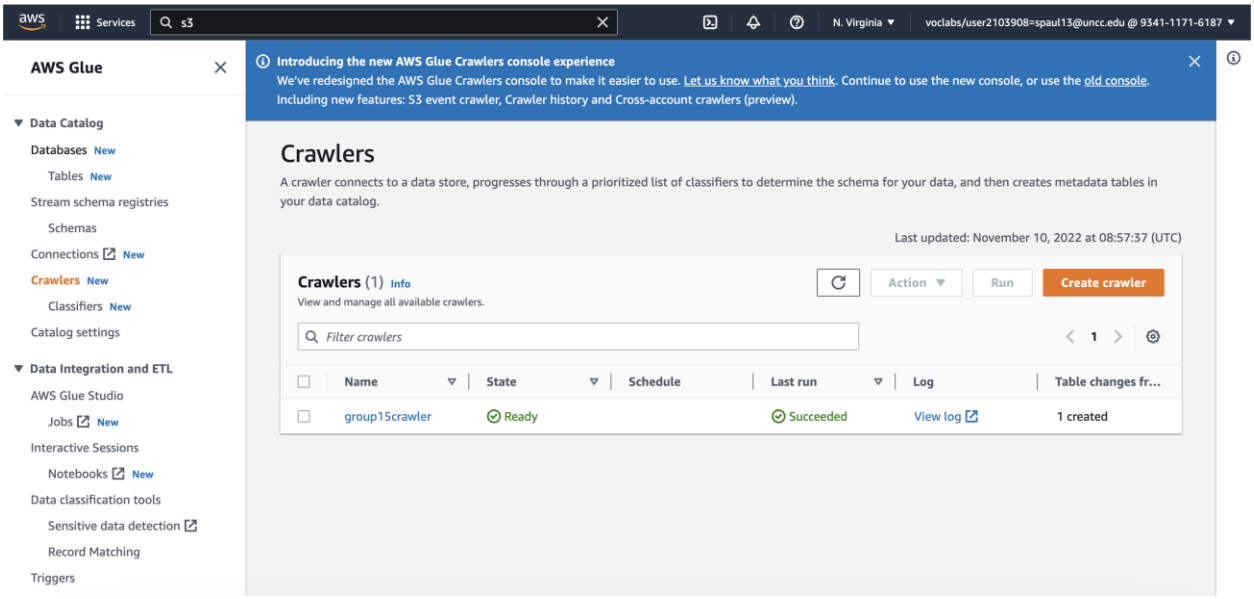
Bucket “group15bucket” has been created and the dataset in csv format was added.

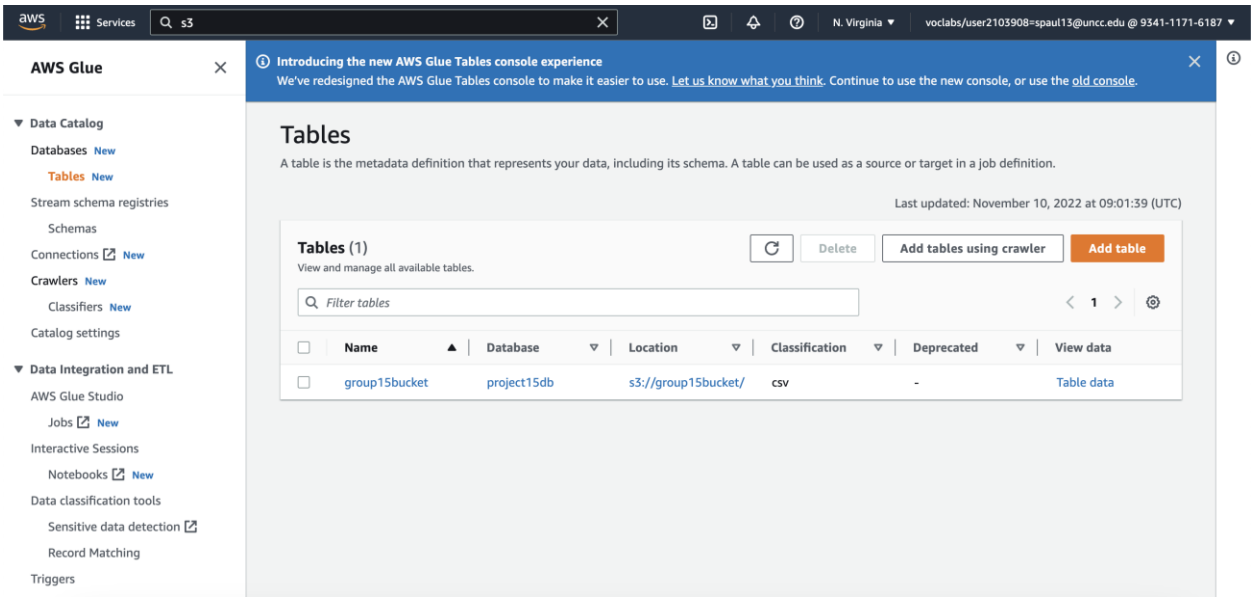




Data Preparation using AWS Glue

Step 1: AWS Glue is used to fetch the data from S3 to AWS Glue.





Properties of the table

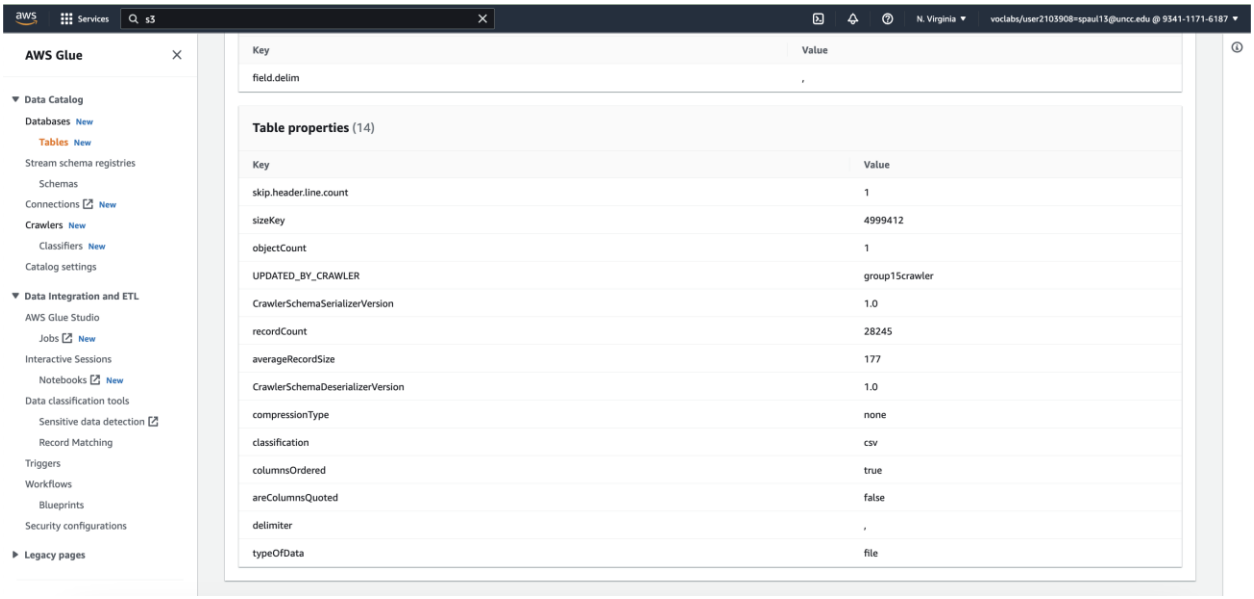
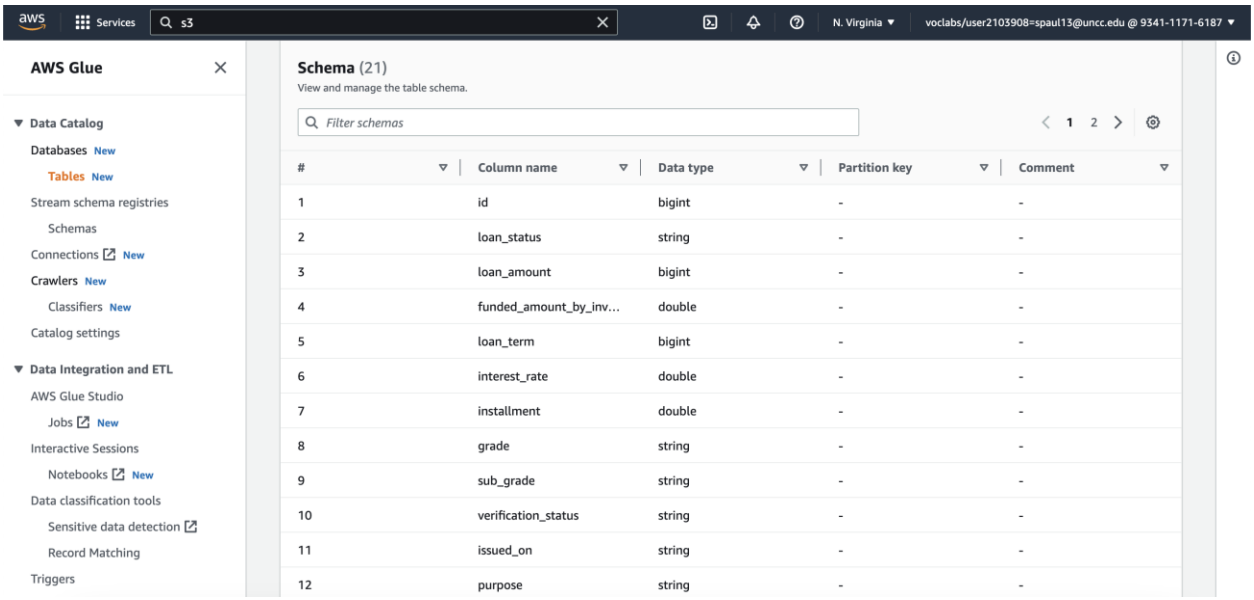
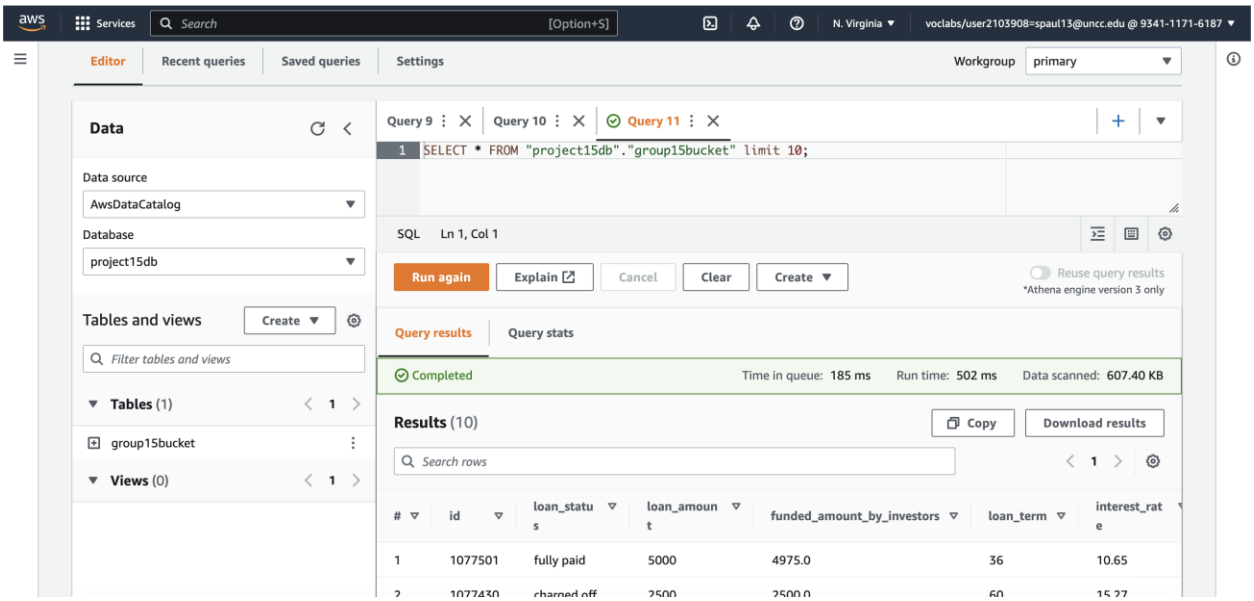
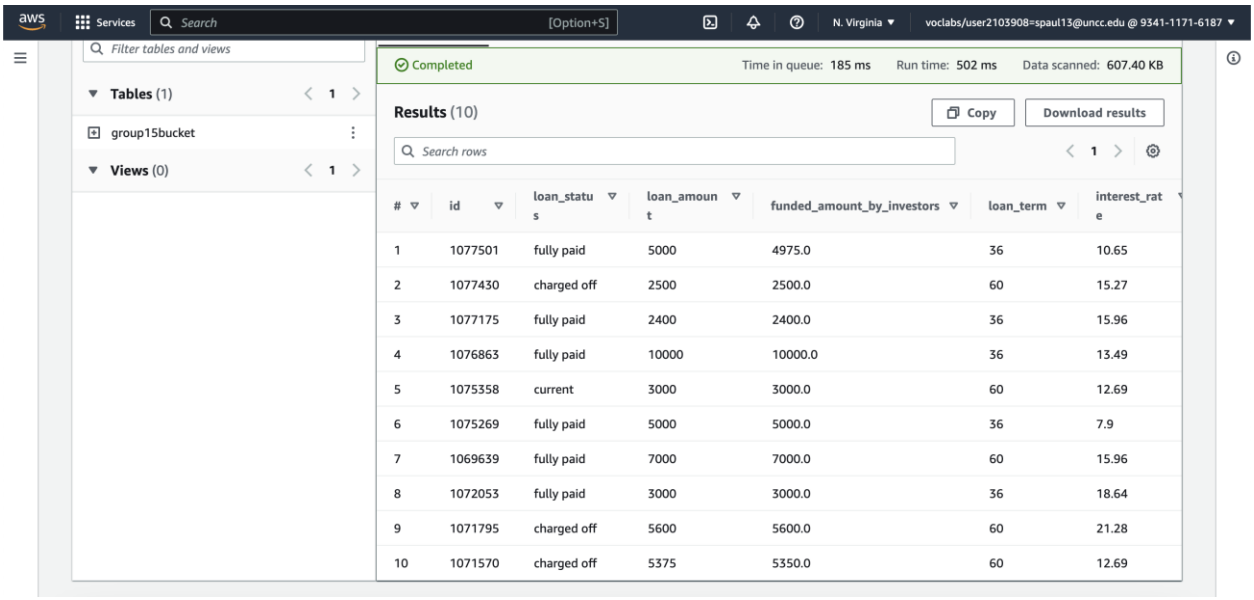


Table Schema



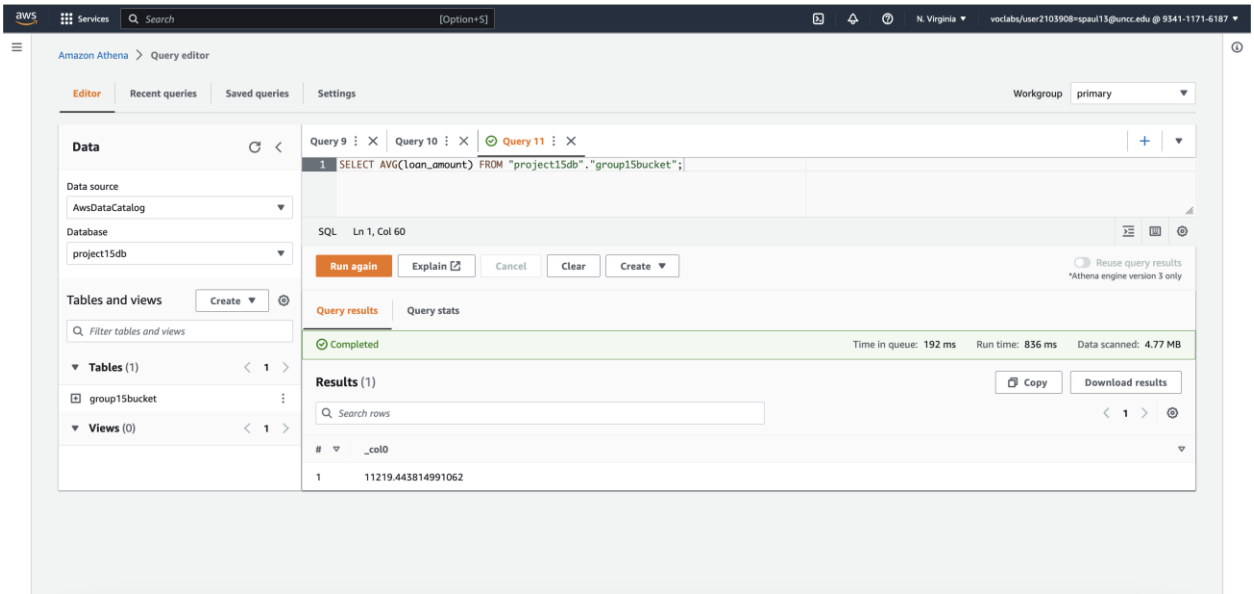
Step 2: Previewed the data on AWS Athena



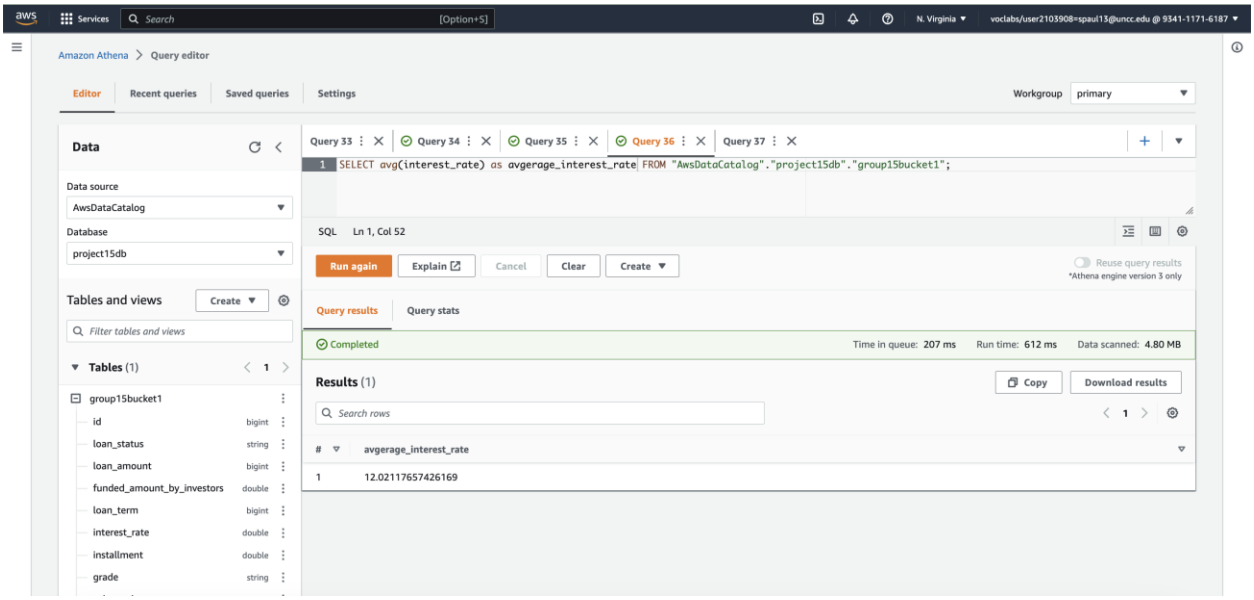


Step 3: Run few SQL queries on AWS Athena for understanding the datasets.

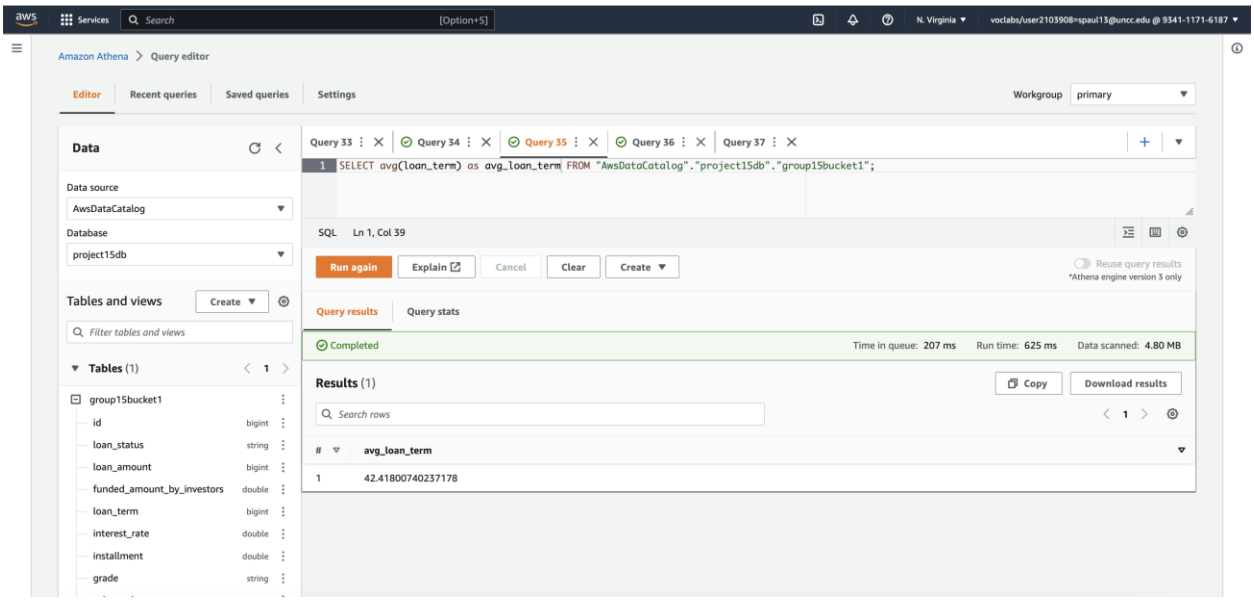
1. Avg of loan amount



2. Avg of interest rate



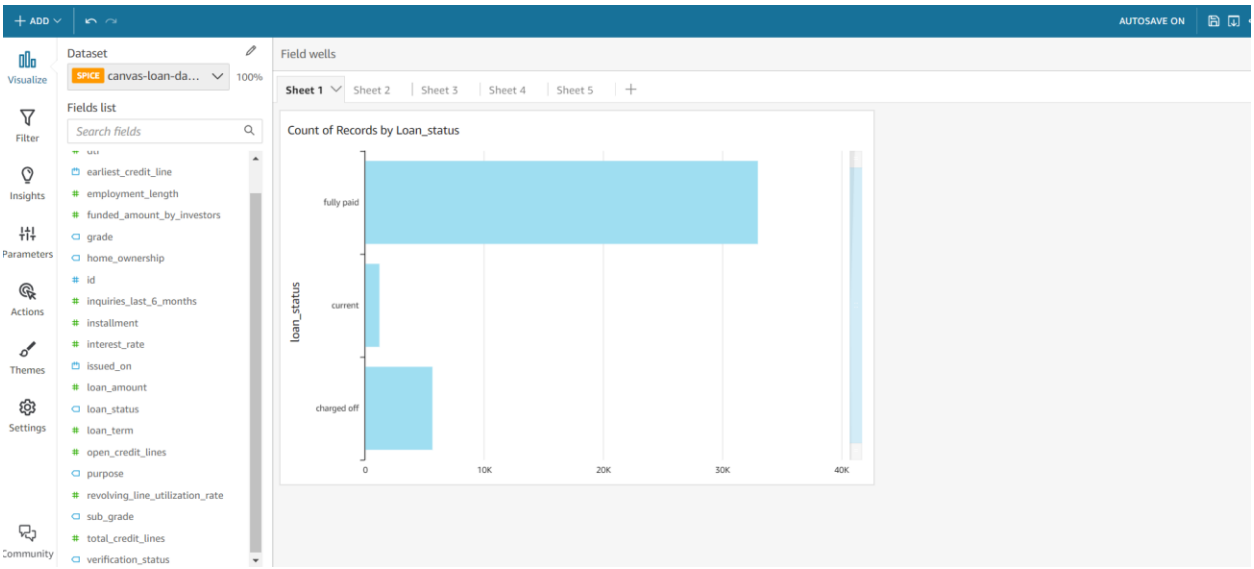
3. Avg of Loan Term



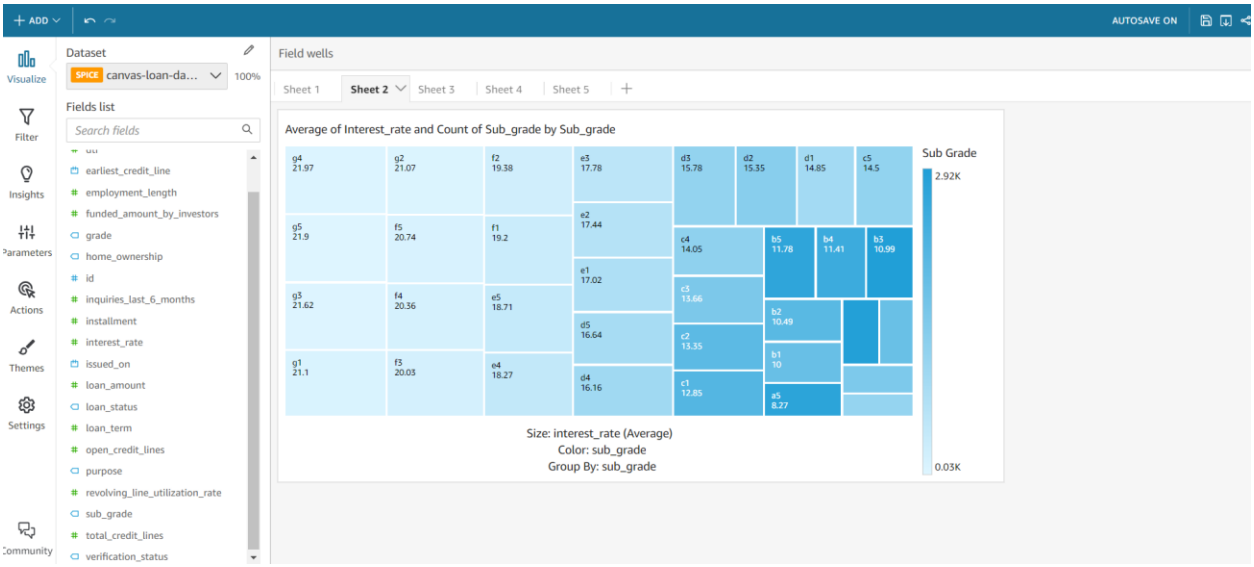
Data Visualization on Quick Sight

The dataset has been visualize on AWS Quick Sight to get a better understanding of the data.

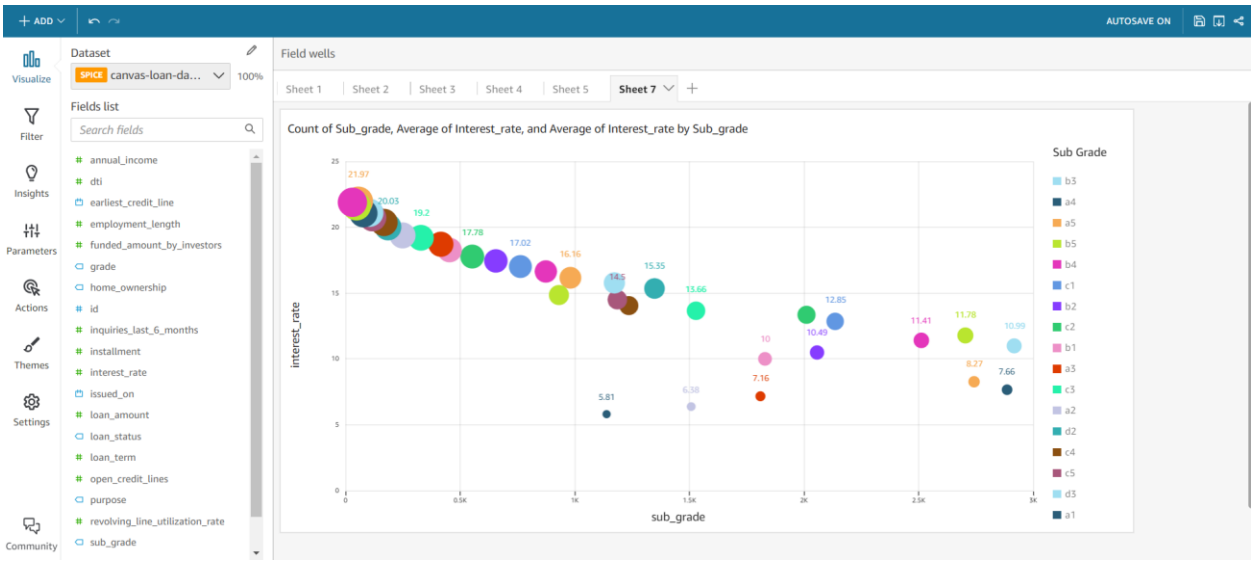
Count of output column (loan_status)



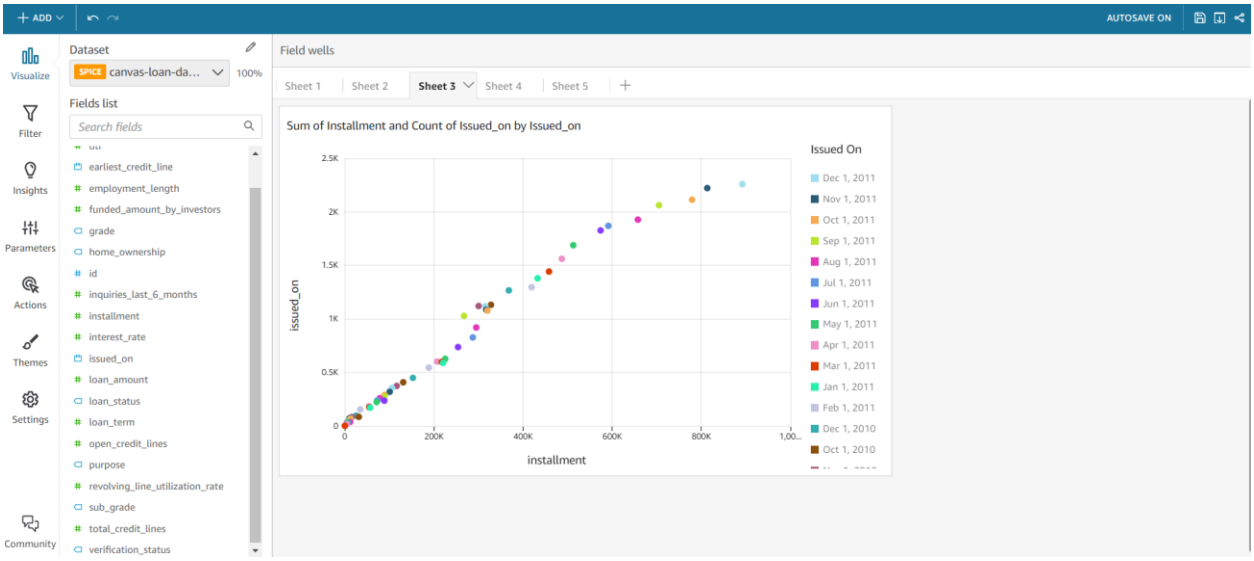
Average of interest rate vs count of sub grade



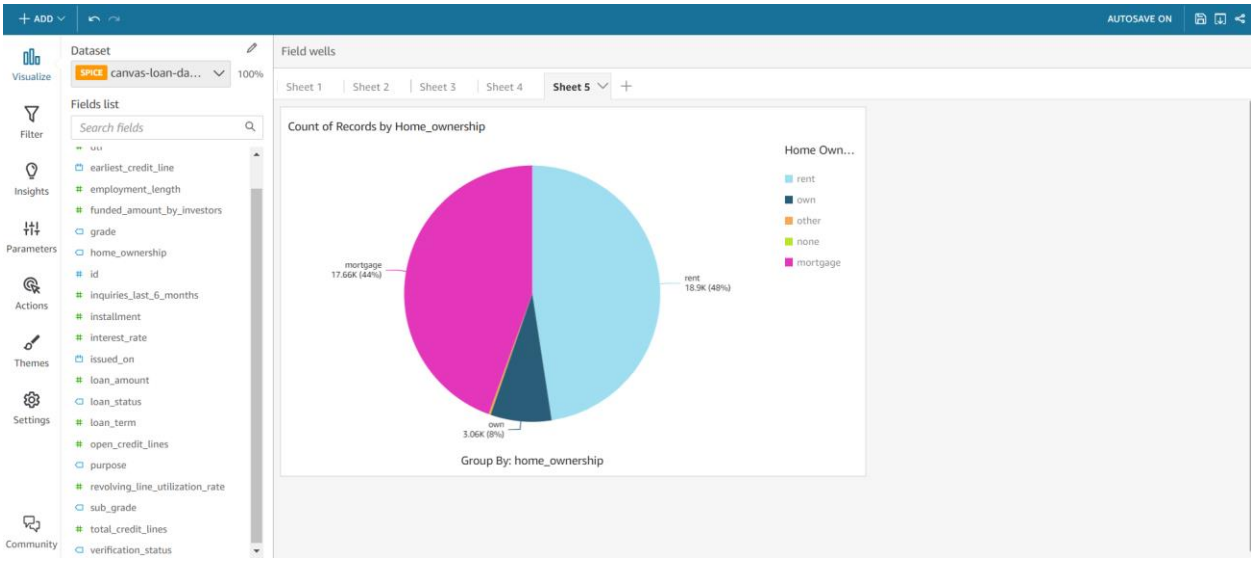
Count of sub grade, average of interest rate and average of interest rate by sub grade.



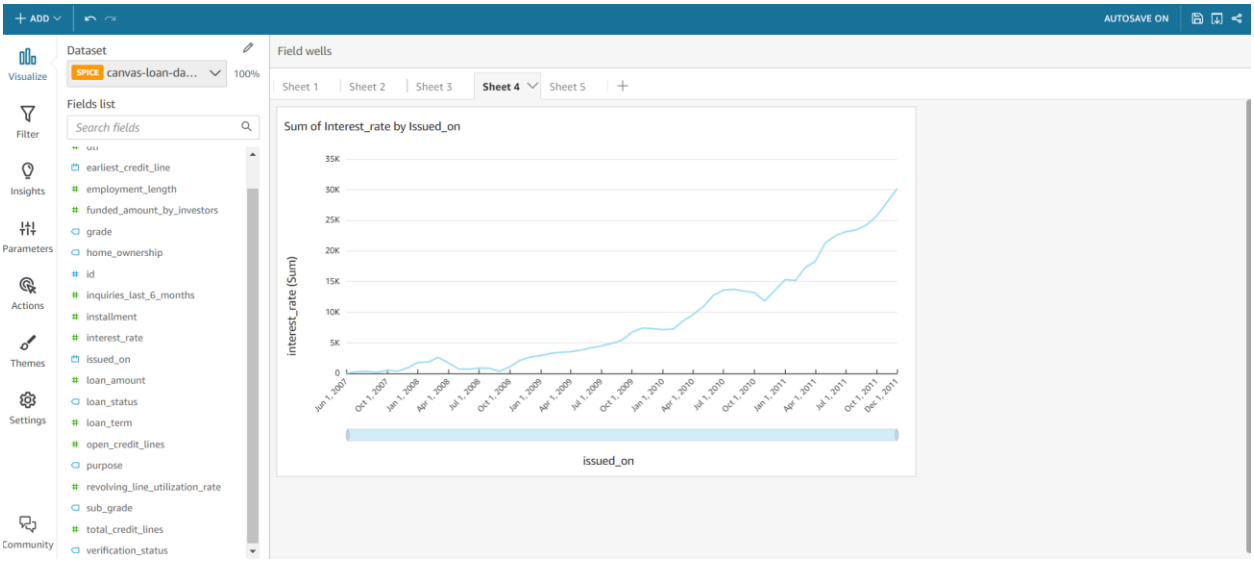
Installment vs count of issued on by date column



Count of records by home ownership

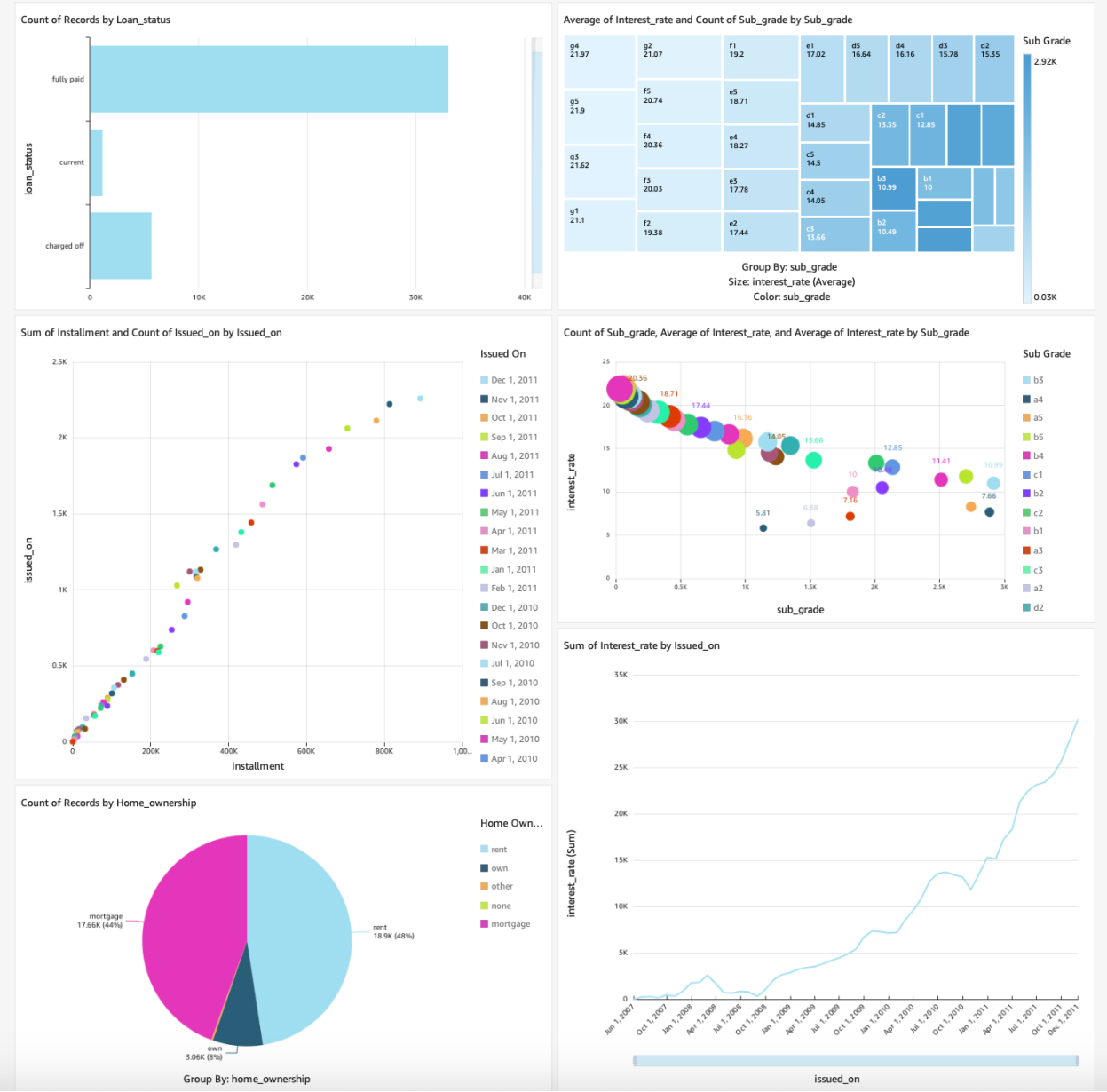


interest rate by date



Quick Sight Dashboard

https://github.com/SoumikPaul108/BigData_Final_Project_Group15/blob/main/Sheet_8_2022-11-14T21_28_53%20(1).pdf



Analytics, Machine Learning

1. XGboost

In [47]:
```
from xgboost import XGBClassifier
```

In [48]:
```
# fit model to training data
model = XGBClassifier()
model.fit(X_train, y_train)
```

Out[48]:
```
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, feature_types=None, gamma=0, gpu_id=-1,
              grow_policy='depthwise', importance_type=None,
              interaction_constraints='', learning_rate=0.300000012,
              max_bin=256, max_cat_threshold=64, max_cat_to_onehot=4,
              max_delta_step=0, max_depth=6, max_leaves=0, min_child_weight=1,
              missing=nan, monotone_constraints='()', n_estimators=100,
              n_jobs=0, num_parallel_tree=1, predictor='auto', random_state=0, ...)
```

In [49]:
```
preds = model.predict(X_test)
```

In [50]:
```
from sklearn.metrics import accuracy_score,plot_confusion_matrix,classification_report
```

In [51]:
```
print(classification_report(y_test,preds))
```

2. Random Forest

Random Forests

In [53]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [54]:
```
rf = RandomForestClassifier(n_estimators=100)
```

In [55]:
```
rf.fit(X_train,y_train)
```

Out[55]:
```
RandomForestClassifier()
```

In [56]:
```
preds = rf.predict(X_test)
```

In [57]:
```
print(classification_report(y_test,preds))
```

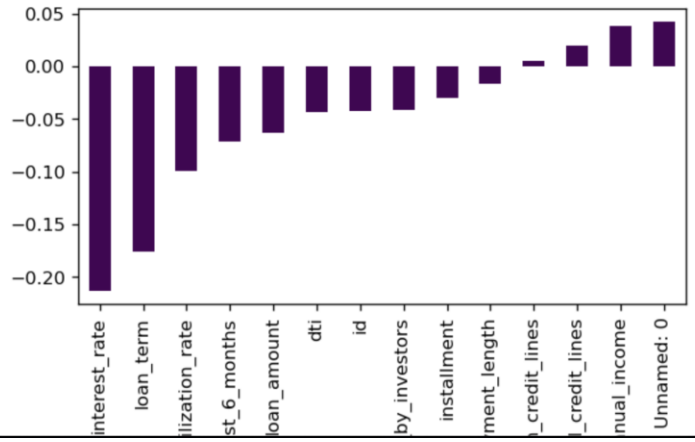
```
              precision    recall  f1-score   support

           0       0.37      0.03      0.05      1049
           1       0.86      0.99      0.92      6451

    accuracy                           0.86      7500
   macro avg       0.62      0.51      0.49      7500
weighted avg       0.79      0.86      0.80      7500
```

Evaluation and Optimization

In [21]:
```
# Create dummies for loan_status so that correlation can be calculated wrt to loan_status
#for other continuous features.
```

In [22]:
```
df_temp = df5.copy() # copy so that it does not affect the original data frame
df_temp['loan_status'] = pd.get_dummies(df_temp['loan_status'], drop_first=True)
```

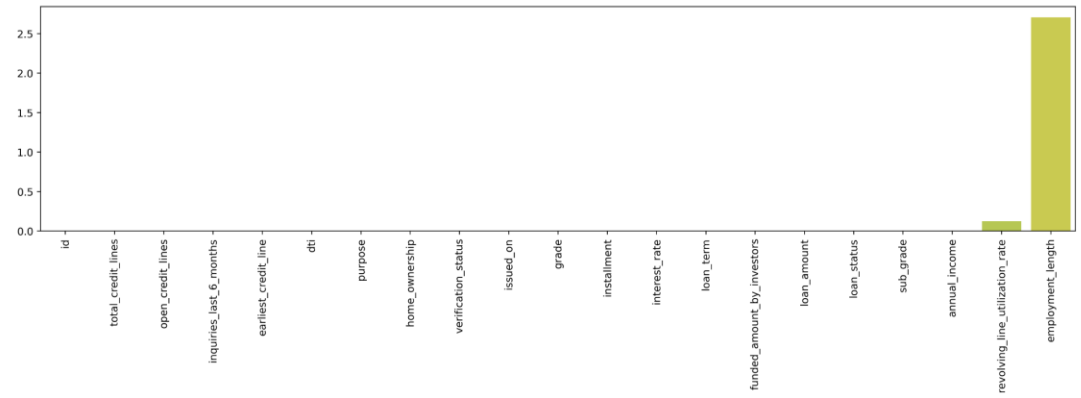
In [23]:
```
plt.figure(figsize=(6,3),dpi=120)
df_temp.corr()['loan_status'].sort_values().drop('loan_status').plot(kind='bar', cmap='viridis') # correlation with loa
plt.xticks(rotation=90);
```



In [24]:
```
# interest_rate, loan_term are highly correlated with loan_status compared to other features.
```

In [25]:
```
# calculate features with missing values.
```

In [26]:
```
plt.figure(figsize=(18,4),dpi=400)
sns.barplot(y=((df.isnull().sum()/len(df))*100).sort_values(), x=((df.isnull().sum()/len(df))*100).sort_values().index,
plt.xticks(rotation=90);
```



In [32]:
```
df5['loan_status'] = df5['loan_status'].map({'fully paid':1,'charged off':0})
df5
```

```
/tmp/ipykernel_11002/87717867.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df5['loan_status'] = df5['loan_status'].map({'fully paid':1,'charged off':0})
```

Out[32]:

	Unnamed: 0	id	loan_status	loan_amount	funded_amount_by_investors	loan_term	interest_rate	installment	grade	sub_grade	...	purpos
0	0	1077501	1	5000	4975.0	36	10.65	162.87	b	b2	...	credit_car
1	1	1077430	0	2500	2500.0	60	15.27	59.83	c	c4	...	ca
2	2	1077175	1	2400	2400.0	36	15.96	84.33	c	c5	...	small_busines
3	3	1076863	1	10000	10000.0	36	13.49	339.31	c	c1	...	othe
5	5	1075269	1	5000	5000.0	36	7.90	156.46	a	a4	...	weddin
...	...	...	...	...	...	...	...	...	...	...	...	.
39712	39712	92187	1	2500	1075.0	36	8.07	78.42	a	a4	...	home_improvemer
39713	39713	90665	1	8500	875.0	36	10.28	275.38	c	c1	...	credit_car
39714	39714	90395	1	5000	1325.0	36	8.07	156.84	a	a4	...	debt_consolidatio
39715	39715	90376	1	5000	650.0	36	7.43	155.38	a	a2	...	othe
39716	39716	87023	1	7500	800.0	36	13.75	255.43	e	e2	...	debt_consolidatio

In [33]:
```
df6=df5[["loan_status","loan_amount","funded_amount_by_investors","loan_term","interest_rate","installment","dti","inqu
df6
```

Out[33]:

	loan_status	loan_amount	funded_amount_by_investors	loan_term	interest_rate	installment	dti	inquiries_last_6_months	open_credit_lines	revolving_li
0	1	5000	4975.0	36	10.65	162.87	27.65	1	3	
1	0	2500	2500.0	60	15.27	59.83	1.00	5	3	
2	1	2400	2400.0	36	15.96	84.33	8.72	2	2	
3	1	10000	10000.0	36	13.49	339.31	20.00	1	10	
5	1	5000	5000.0	36	7.90	156.46	11.20	3	9	
...	...	...	...	...	...	...	...	...	...	
39712	1	2500	1075.0	36	8.07	78.42	11.33	0	13	
39713	1	8500	875.0	36	10.28	275.38	6.40	1	6	
39714	1	5000	1325.0	36	8.07	156.84	2.30	0	11	
39715	1	5000	650.0	36	7.43	155.38	3.72	0	17	
39716	1	7500	800.0	36	13.75	255.43	14.29	0	7	

37497 rows × 13 columns

Results

XGBoost

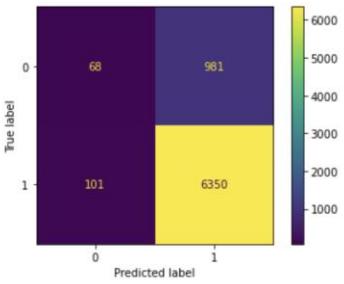
In [51]:
```
print(classification_report(y_test,preds))
```

```
              precision    recall  f1-score   support

           0       0.40      0.06      0.11      1049
           1       0.87      0.98      0.92      6451

    accuracy                           0.86      7500
   macro avg       0.63      0.52      0.52      7500
weighted avg       0.80      0.86      0.81      7500
```

In [52]:
```
plot_confusion_matrix(model,X_test,y_test)
```

```
/home/ec2-user/anaconda3/envs/python3/lib/python3.8/site-packages/sklearn/utils/deprecation.py:87: FutureWarning: Fun
ction plot_confusion_matrix is deprecated; Function `plot_confusion_matrix` is deprecated in 1.0 and will be removed
in 1.2. Use one of the class methods: ConfusionMatrixDisplay.from_predictions or ConfusionMatrixDisplay.from_estimato
r.
  warnings.warn(msg, category=FutureWarning)
```

Out[52]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f4f5b059280>
```



Random Forest

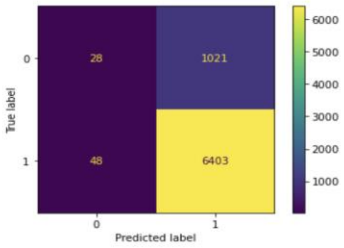
In [57]:
```
print(classification_report(y_test,preds))
```

```
              precision    recall  f1-score   support

           0       0.37      0.03      0.05      1049
           1       0.86      0.99      0.92      6451

    accuracy                           0.86      7500
   macro avg       0.62      0.51      0.49      7500
weighted avg       0.79      0.86      0.80      7500
```

In [58]:
```
plot_confusion_matrix(rf,X_test,y_test)
```

```
/home/ec2-user/anaconda3/envs/python3/lib/python3.8/site-packages/sklearn/utils/deprecation.py:87: FutureWarning: Fun
ction plot_confusion_matrix is deprecated; Function `plot_confusion_matrix` is deprecated in 1.0 and will be removed
in 1.2. Use one of the class methods: ConfusionMatrixDisplay.from_predictions or ConfusionMatrixDisplay.from_estimato
r.
  warnings.warn(msg, category=FutureWarning)
```

Out[58]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f4f4596ae20>
```



Future Work

What was unique about the data? Did you have to deal with imbalance?

The entire dataset has around 40k rows and 21 columns. The dataset was split into two halves. As a result, we had to conduct an inner join operation on the datasets in order to operate on only one.

What data cleaning did you do? Outlier treatment? Imputation?

First, we determined the percentage of null values in each column, ordered in descending order of missing values; "employment length" was the sole column with 2.7% of the null value. Second, we view the null values and drop them entirely.

Did you create any new additional features / variables?

We have not added any additional features. Only the features and functionality described in the instructions and AWS labs have been preserved in the project.

What was the process you used for evaluation? What was the best result?

Our machine learning model was constructed using the XGboost and Random Forest algorithms. In the case of XGboost, we reached 86% accuracy, and in the case of Random Forest, we also achieved 86% accuracy. Using both techniques, we were able to obtain the same accuracy.

Is there Bias in your work? What were the problems you faced? How did you solve them?

The only challenge we had was that all the text columns' data became corrupt when we uploaded our information to AWS Athena via AWS Glue, while all of the integer and double columns' data remained in pristine condition. Initial inquiries were successful; however, the dataset began to display erroneous data after a few AWS Athena queries. The dataset, however, worked flawlessly when visualized using AWS Glue.

What future work would you like to do?

To determine how many of the current loans were paid off, defaulted on, or even charged off, we may utilize an updated data frame that includes the numbers for the next three years (2007-2011). These new data points can then be utilized for forecasting or for developing new models.

In order to improve the model's ability to anticipate competent borrowers, we may wish to look into this matter more since the algorithm places about 36% of non-defaulters in the default class.

Instructions for individuals that may want to use your work

LendingClub must use caution when finding potential borrowers who meet specific requirements. Borrowers who do not own a home, for example, and apply for a small company or wedding loan may have a bad combination that leads to the borrower defaulting on a future loan.

LendingClub must be aware that low-graded loans are undoubtedly more likely to default. They must be prepared to collaborate with these borrowers to secure appropriate and timely payments. Reduced interest rates or installment payments for these consumers might be beneficial.