Capstone project: Providing data-driven suggestions for HR

- The stakeholder is the HR department at Salifort Motors.
- The task is to create a predictive model and use it to assist the department in identifying employees in risk of leaving the company.
- The dataset contains observations relevant to the task.
- There's no information in the dataset for observations that represent different groups in the workplace.

Import packages

In [ ]:
```
# Import packages
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

from xgboost import XGBClassifier

from xgboost import plot_importance
```

Load dataset

In [ ]:
```
# Load dataset into a dataframe
df0 = pd.read_csv("HR_capstone_dataset.csv")

# Display first few rows of the dataframe
df0.head()
```

Out[ ]:

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spend_co
0	0.38	0.53	2	157	
1	0.80	0.86	5	262	
2	0.11	0.88	7	272	
3	0.72	0.87	5	223	
4	0.37	0.52	2	159	

Step 2. Data Exploration (Initial EDA and data cleaning)

Gather basic information about the data

In [ ]:
```
# Gather basic information about the data
df0.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14999 entries, 0 to 14998
Data columns (total 10 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   satisfaction_level     14999 non-null  float64
 1   last_evaluation        14999 non-null  float64
 2   number_project         14999 non-null  int64  
 3   average_montly_hours   14999 non-null  int64  
 4   time_spend_company     14999 non-null  int64  
 5   Work_accident          14999 non-null  int64  
 6   left                   14999 non-null  int64  
 7   promotion_last_5years  14999 non-null  int64  
 8   Department             14999 non-null  object 
 9   salary                 14999 non-null  object 
dtypes: float64(2), int64(6), object(2)
memory usage: 1.1+ MB
```

Gather descriptive statistics about the data

In [ ]:
```
# Gather descriptive statistics about the data
df0.describe(include='all')
```

Out[ ]:

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spe
count	14999.000000	14999.000000	14999.000000	14999.000000	1
unique	NaN	NaN	NaN	NaN	
top	NaN	NaN	NaN	NaN	
freq	NaN	NaN	NaN	NaN	
mean	0.612834	0.716102	3.803054	201.050337	
std	0.248631	0.171169	1.232592	49.943099	
min	0.090000	0.360000	2.000000	96.000000	
25%	0.440000	0.560000	3.000000	156.000000	
50%	0.640000	0.720000	4.000000	200.000000	
75%	0.820000	0.870000	5.000000	245.000000	
max	1.000000	1.000000	7.000000	310.000000	

Rename columns

As a data cleaning step, rename the columns as needed. Standardize the column names so that they are all in `snake_case`, correct any column names that are misspelled, and make column names more concise as needed.

In [ ]:
```
# Display all column names
df0.columns
```

Out[ ]:
```
Index(['satisfaction_level', 'last_evaluation', 'number_project',
       'average_montly_hours', 'time_spend_company', 'Work_accident', 'left',
       'promotion_last_5years', 'Department', 'salary'],
      dtype='object')
```

In [ ]:
```
# Rename columns as needed
df0.rename(columns = {'satisfaction_level': 'satisfaction',
                      'number_project': 'projects',
                      'average_montly_hours': 'avg_monthly_hours',
                      'time_spend_company': 'tenure',
                      'Work_accident': 'accidents',
                      'left': 'churn',
                      'promotion_last_5years': 'promoted',
                      'Department': 'department',
                      'salary': 'compensation'}, inplace = True)

# Display all column names after the update
df0.columns
```

Out[ ]:
```
Index(['satisfaction', 'last_evaluation', 'projects', 'avg_monthly_hours',
       'tenure', 'accidents', 'churn', 'promoted', 'department',
       'compensation'],
      dtype='object')
```

Check missing values

Check for any missing values in the data.

In [ ]:
```
# Check for missing values
df0.isna().sum()
```

Out[ ]:
```
satisfaction         0
last_evaluation      0
projects             0
avg_monthly_hours    0
tenure               0
accidents            0
churn                0
promoted             0
department           0
compensation         0
dtype: int64
```

Check for duplicates

In [ ]:
```
# Check for duplicates
dp_mask = df0.duplicated()
dp_mask
```

Out[ ]:
```
0        False
1        False
2        False
3        False
4        False
         ...
14994     True
14995     True
14996     True
14997     True
14998     True
Length: 14999, dtype: bool
```

In [ ]:
```
# Inspect some rows containing duplicates as needed
df0[dp_mask]
```

Out[ ]:

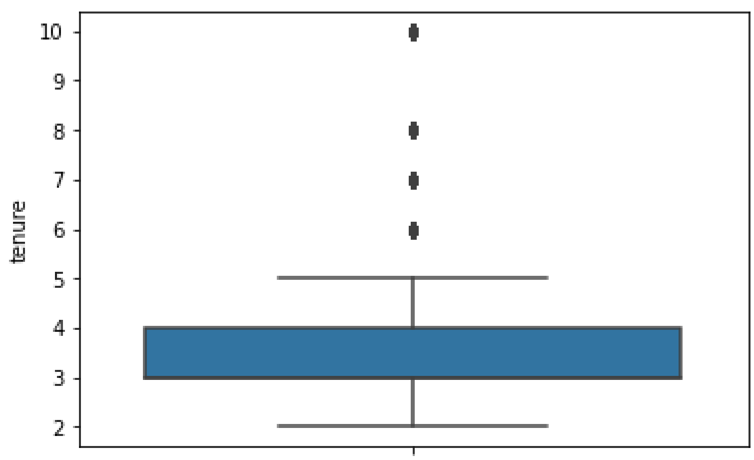
	satisfaction	last_evaluation	projects	avg_monthly_hours	tenure	accidents	churn
396	0.46	0.57	2	139	3	0	1
866	0.41	0.46	2	128	3	0	1
1317	0.37	0.51	2	127	3	0	1
1368	0.41	0.52	2	132	3	0	1
1461	0.42	0.53	2	142	3	0	1
...	...	...	...	...	...	...	...
14994	0.40	0.57	2	151	3	0	1
14995	0.37	0.48	2	160	3	0	1
14996	0.37	0.53	2	143	3	0	1
14997	0.11	0.96	6	280	4	0	1
14998	0.37	0.52	2	158	3	0	1

3008 rows × 10 columns

Check for outliers

In [ ]:
```
# Create a boxplot to visualize distribution of `tenure` and detect any outliers
sns.boxplot(y = df0['tenure'])
```

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb0f8272cd0>



In [ ]:
```
# Determine the number of rows containing outliers
percentile_25 = df0['tenure'].quantile(0.25)
percentile_75 = df0['tenure'].quantile(0.75)
iqr = percentile_75 - percentile_25

upper_limit = percentile_75 + 1.5 * iqr
```

```
df0[df0['tenure'] > upper_limit]
```

Out[ ]:

	satisfaction	last_evaluation	projects	avg_monthly_hours	tenure	accidents	churn
1	0.80	0.86	5	262	6	0	1
17	0.78	0.99	4	255	6	0	1
34	0.84	0.87	4	246	6	0	1
47	0.57	0.70	3	273	6	0	1
67	0.90	0.98	4	264	6	0	1
...	...	...	...	...	...	...	...
14942	0.20	0.50	5	135	6	0	1
14947	0.91	0.98	4	242	6	0	1
14977	0.81	0.85	4	251	6	0	1
14986	0.85	0.85	4	247	6	0	1
14993	0.76	0.83	6	293	6	0	1

1282 rows × 10 columns

Step 2. Data Exploration (Continue EDA)

In [ ]:

```
# Get numbers of people who left vs. stayed
left = df0[df0['churn'] == 1].count()[0]
stayed = df0[df0['churn'] == 0].count()[0]

print("Employees left: {:>6}".format(left))
print("Employees stayed: {}".format(stayed))

# Get percentages of people who left vs. stayed
print("Employees left: {:>4.0f}%".format((left/df0.shape[0])*100))
print("Employees stayed: {:.0f}%".format((stayed/df0.shape[0])*100))
```

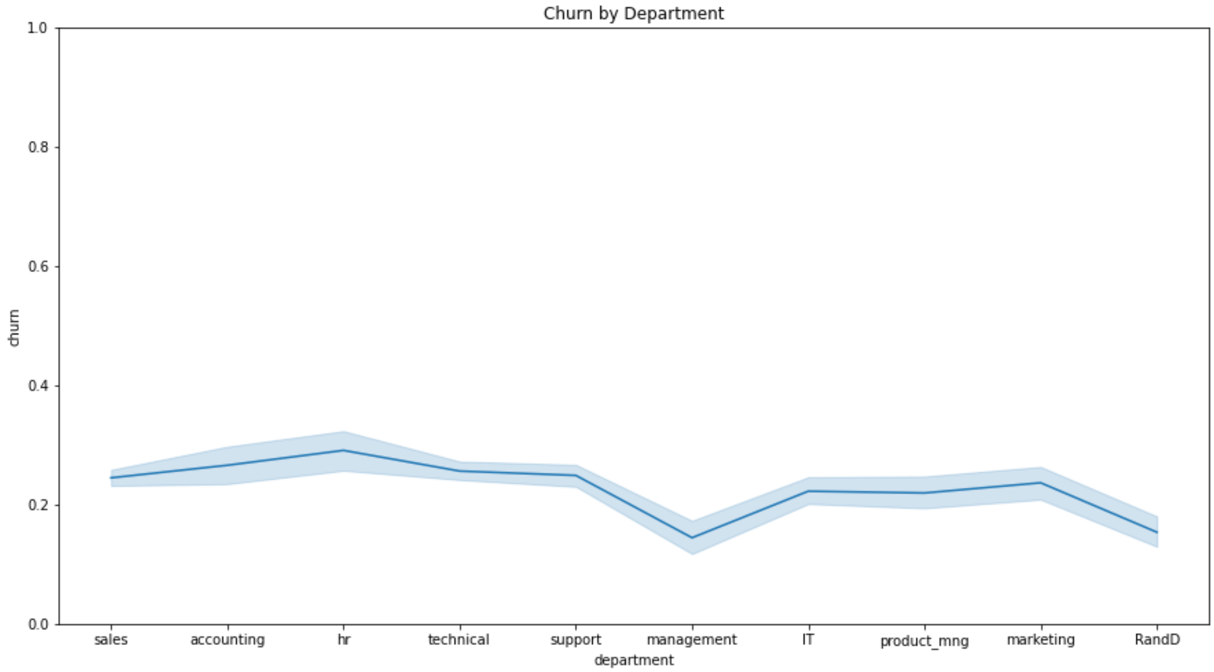
```
Employees left:   3571
Employees stayed: 11428
Employees left:   24%
Employees stayed: 76%
```

Data visualizations

In [ ]:

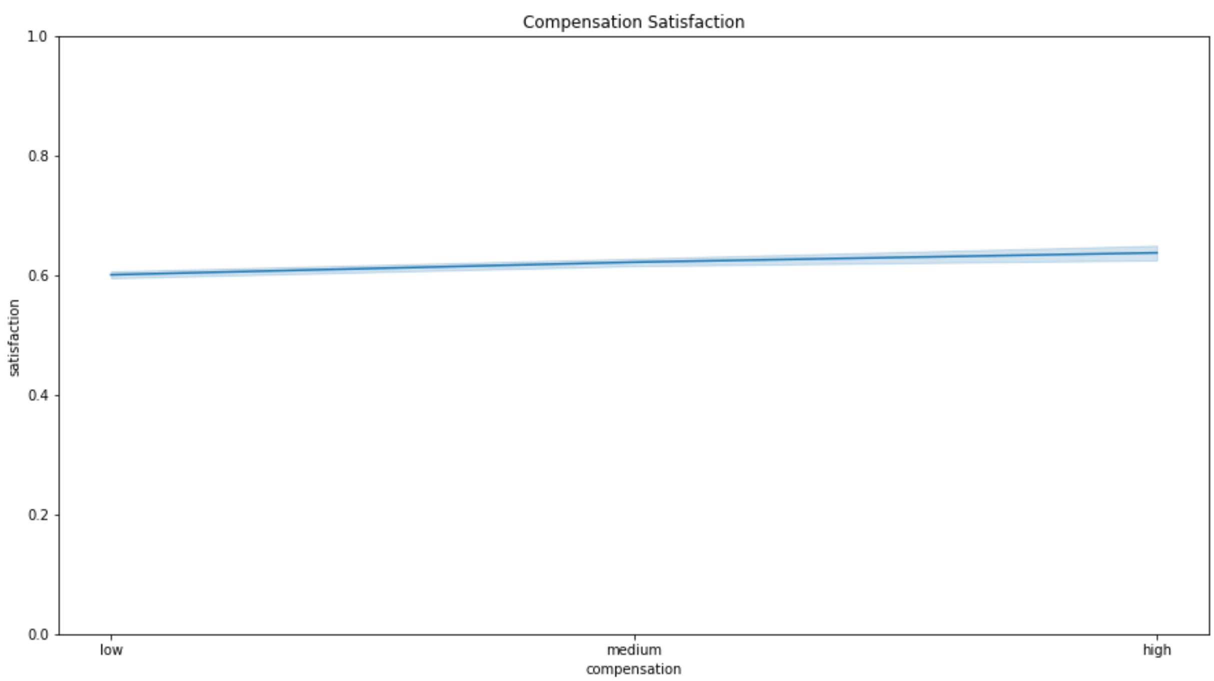
```
# Create a plot as needed
plt.figure(figsize=(15,8))
v = sns.lineplot(x = df0['department'], y = df0['churn'])
v.set_title('Churn by Department')
v.set(ylim=(0, max(df0['churn'])))
```

Out[ ]: [(0.0, 1.0)]



In [ ]:
```
# Create a plot as needed
plt.figure(figsize=(15,8))
v = sns.lineplot(x = df0['compensation'], y = df0['satisfaction'])
v.set_title('Compensation Satisfaction')
v.set(ylim=(0, max(df0['satisfaction'])))
```

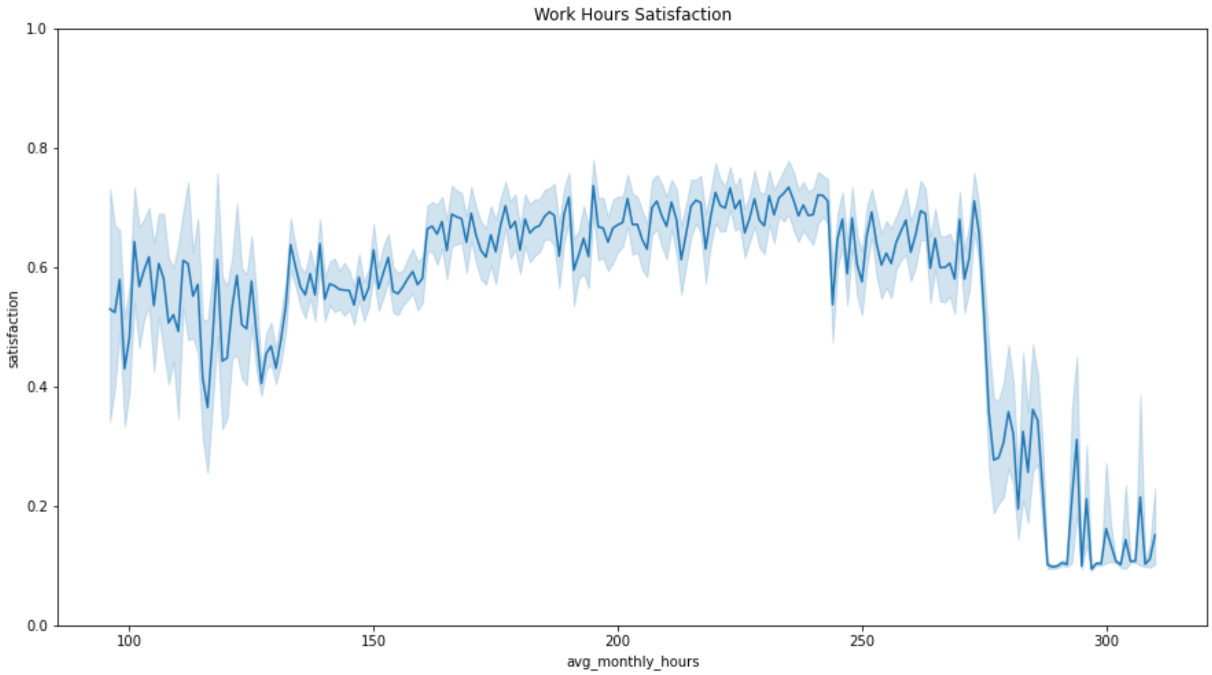
Out[ ]: [(0.0, 1.0)]



In [ ]:
```
# Create a plot as needed
plt.figure(figsize=(15,8))
v = sns.lineplot(x = df0['avg_monthly_hours'], y = df0['satisfaction'])
```

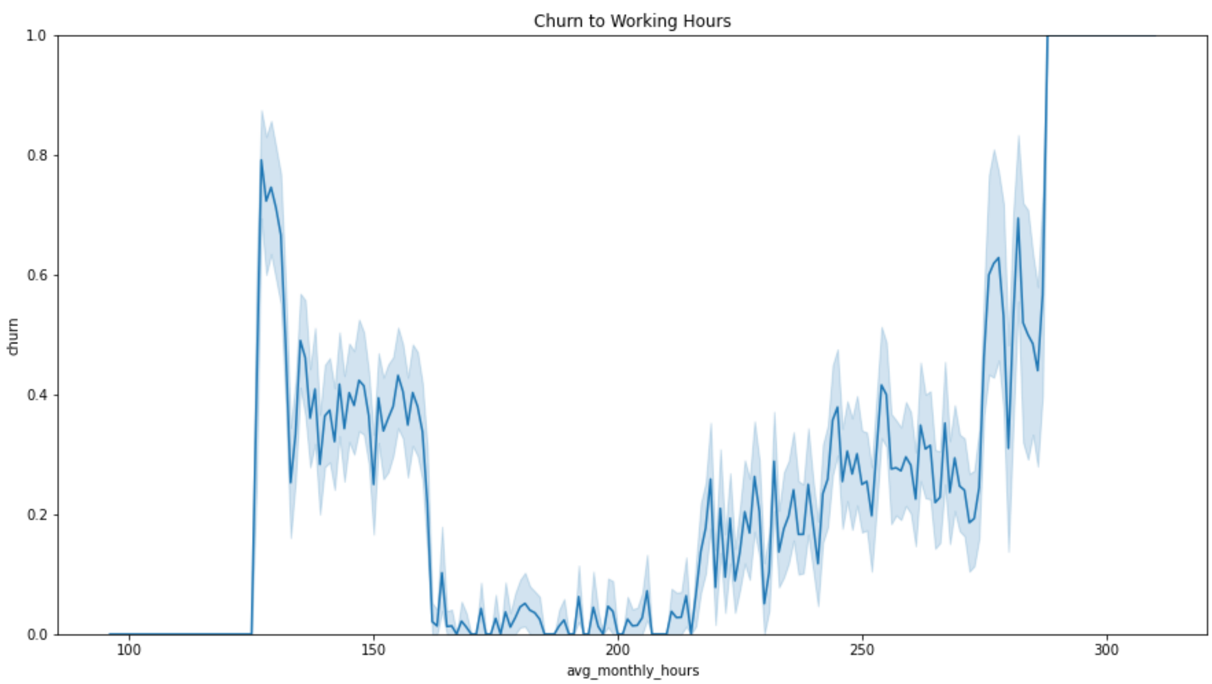
```python
v.set_title('Work Hours Satisfaction')
v.set(ylim=(0, max(df0['satisfaction'])))
```

Out[ ]: `[(0.0, 1.0)]`



In [ ]:
```python
# Create a plot as needed
plt.figure(figsize=(15,8))
v = sns.lineplot(x = df0['avg_monthly_hours'], y = df0['churn'])
v.set_title('Churn to Working Hours')
v.set(ylim=(0, max(df0['churn'])))
```

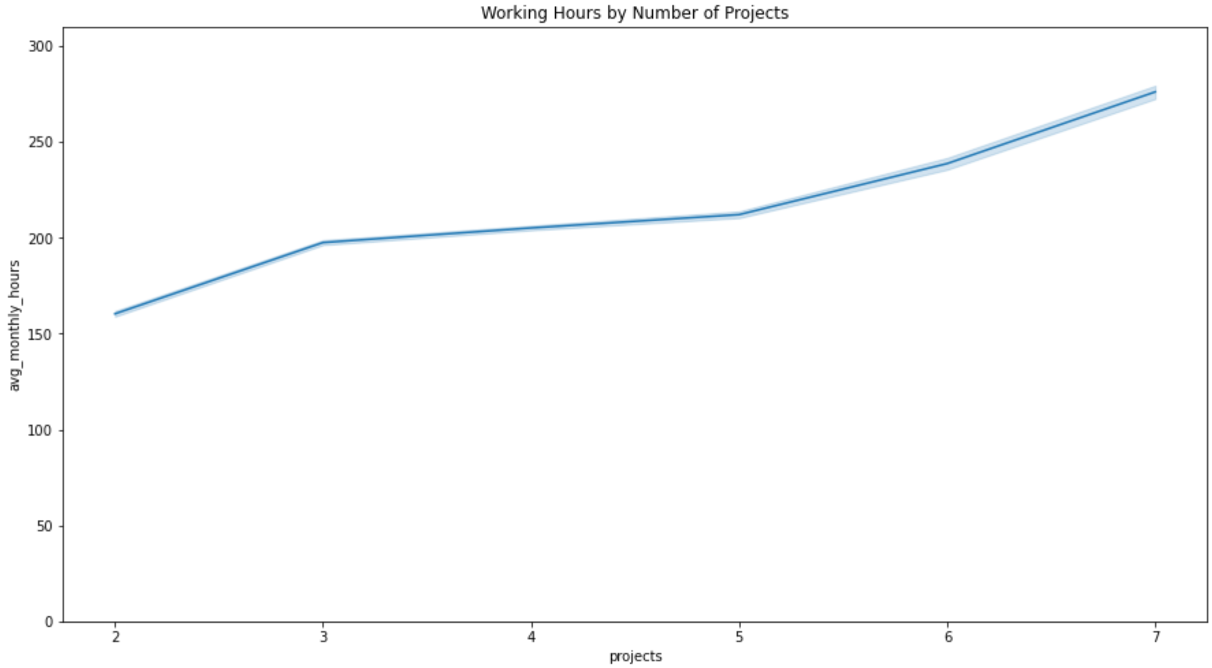
Out[ ]: `[(0.0, 1.0)]`



In [ ]:
```python
# Create a plot as needed
plt.figure(figsize=(15,8))
```

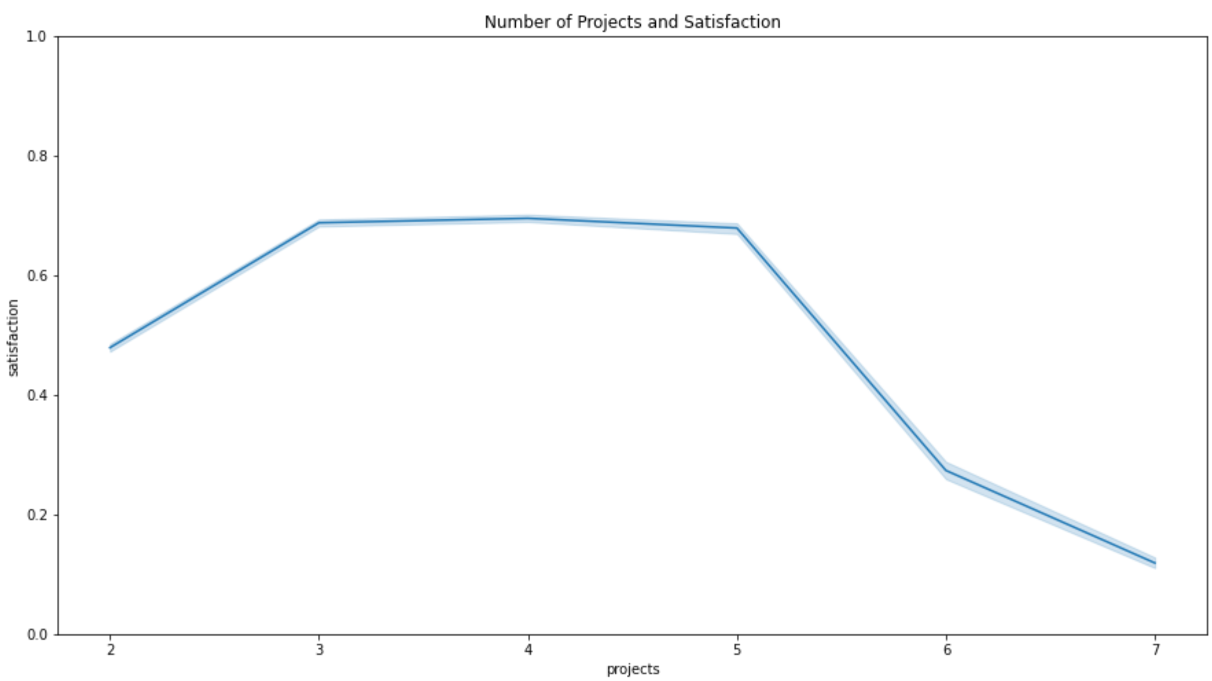
```
v = sns.lineplot(x = df0['projects'], y = df0['avg_monthly_hours'])
v.set_title('Working Hours by Number of Projects')
v.set(ylim=(0, max(df0['avg_monthly_hours'])))
```

Out[ ]: [(0.0, 310.0)]



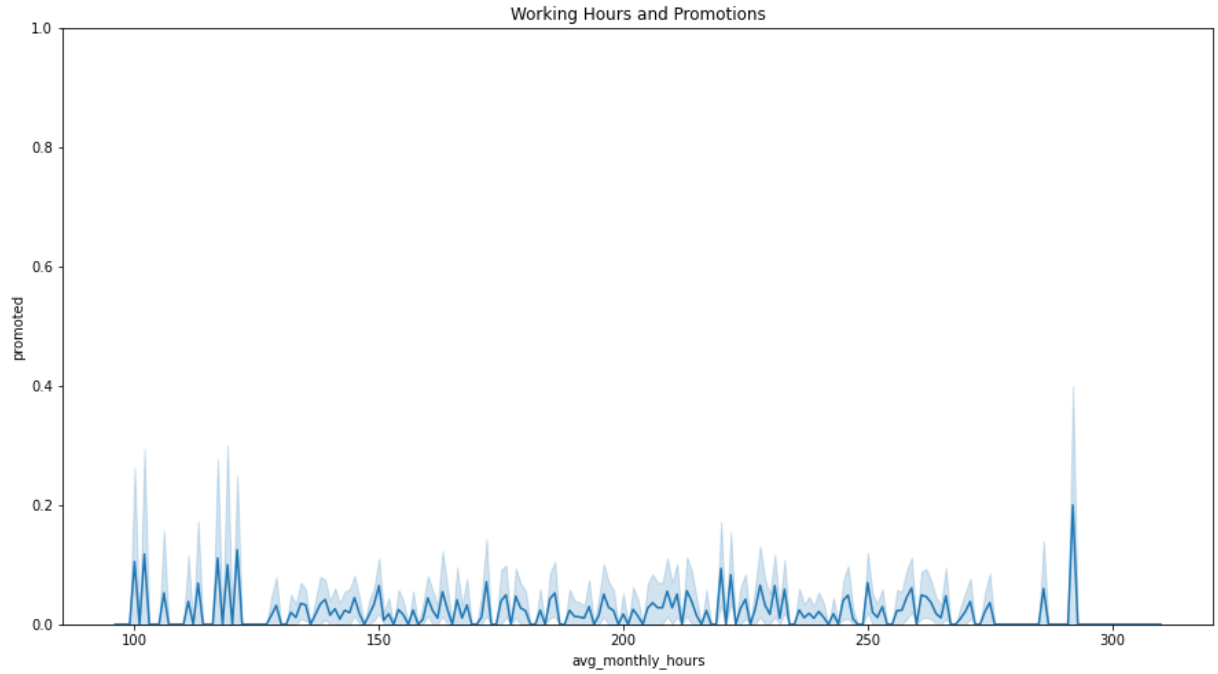
In [ ]:
```
# Create a plot as needed
plt.figure(figsize=(15,8))
v = sns.lineplot(x = df0['projects'], y = df0['satisfaction'])
v.set_title('Number of Projects and Satisfaction')
v.set(ylim=(0, max(df0['satisfaction'])))
```

Out[ ]: [(0.0, 1.0)]



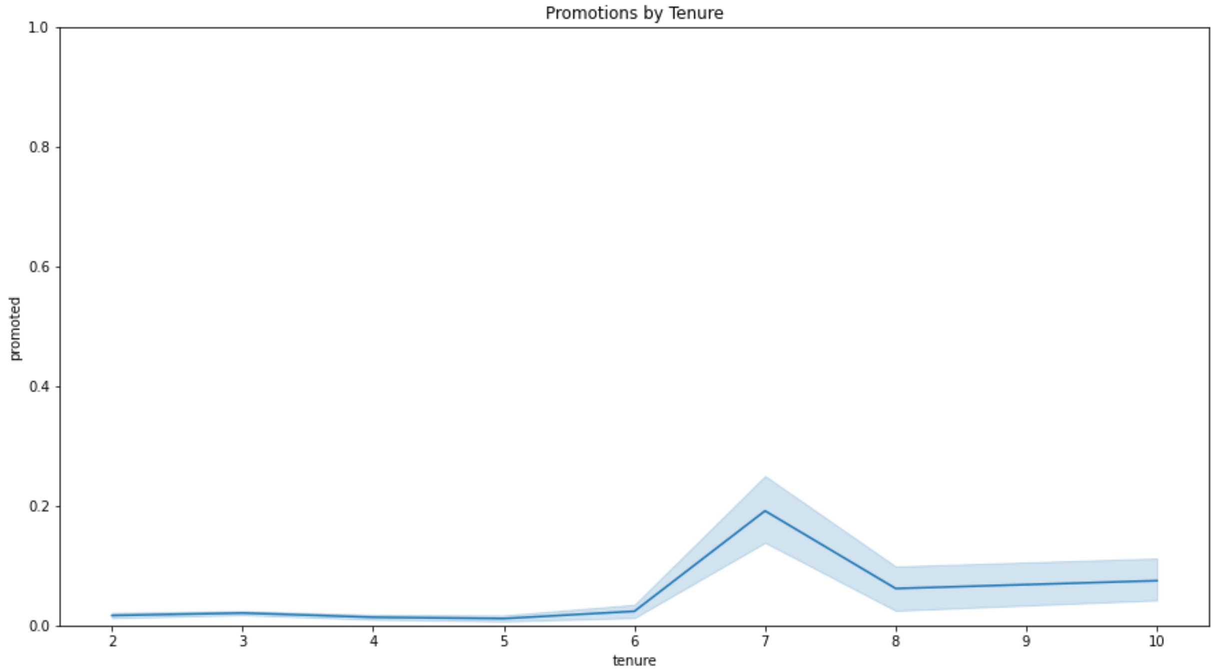
In [ ]:
```
# Create a plot as needed
plt.figure(figsize=(15,8))
v = sns.lineplot(x = df0['avg_monthly_hours'], y = df0['promoted'])
v.set_title('Working Hours and Promotions')
v.set(ylim=(0, max(df0['promoted'])))
```

Out[ ]: [(0.0, 1.0)]



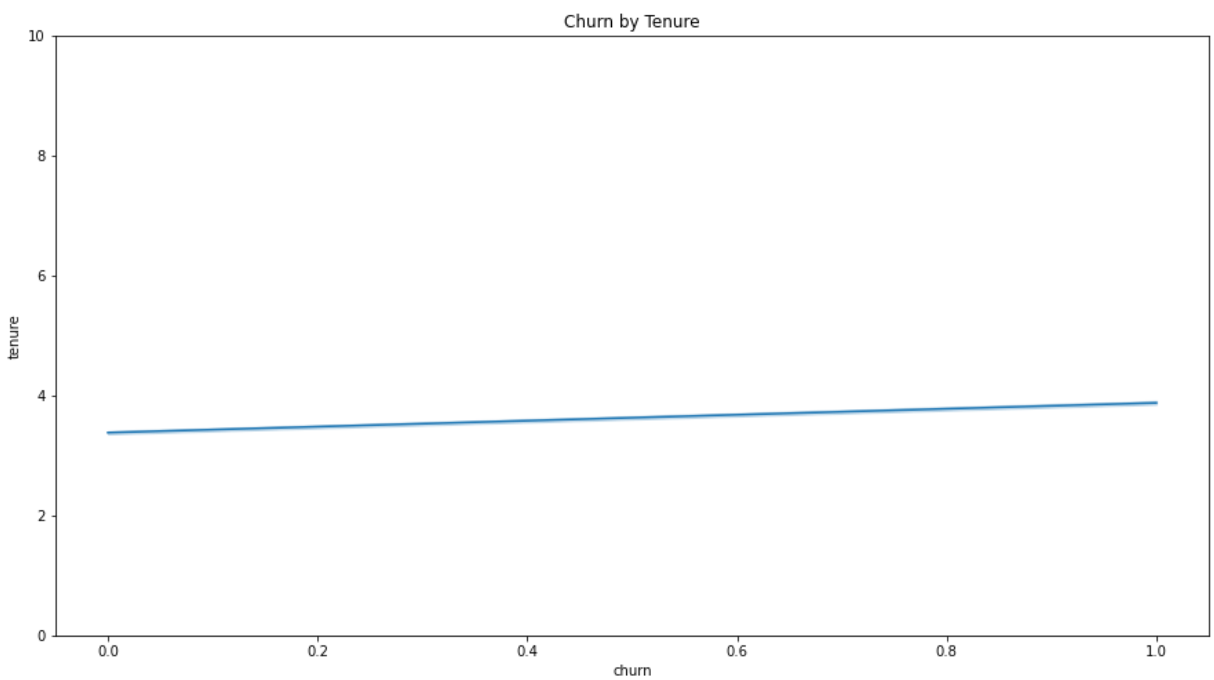
In [ ]:
```
# Create a plot as needed
plt.figure(figsize=(15,8))
v = sns.lineplot(x = df0['tenure'], y = df0['promoted'])
v.set_title('Promotions by Tenure')
v.set(ylim=(0, max(df0['promoted'])))
```

Out[ ]: [(0.0, 1.0)]



In [ ]:
```
# Create a plot as needed
plt.figure(figsize=(15,8))
v = sns.lineplot(x = df0['churn'], y = df0['tenure'])
v.set_title('Churn by Tenure')
v.set(ylim=(0, max(df0['tenure'])))
```

Out[ ]: [(0.0, 10.0)]



Insights

- There's strong correlation between average work hours, number of projects, satisfaction and churn.

Step 3. Model Building, Step 4. Results and Evaluation

Modeling

In [ ]:
```
# Selecting features
df = df0.drop(['compensation', 'department', 'accidents', 'last_evaluation'], axis=
df.head(5)
```

Out[ ]:

	satisfaction	projects	avg_monthly_hours	tenure	churn	promoted
0	0.38	2	157	3	1	0
1	0.80	5	262	6	1	0
2	0.11	7	272	4	1	0
3	0.72	5	223	5	1	0
4	0.37	2	159	3	1	0

In [ ]:
```
# Splitting data
y = df['churn']
X = df.drop(columns=['churn'])

X_tr, X_test, y_tr, y_test = train_test_split(X, y, test_size = 0.3, stratify=y)
X_train, X_val, y_train, y_val = train_test_split(X_tr, y_tr, stratify=y_tr, test_s
```

In [ ]:
```
# XGBoost Model construction
xgb = XGBClassifier(objective='binary:logistic', random_state=42)
cv_params = {'max_depth': [6, 12],
             'min_child_weight': [3, 5],
             'learning_rate': [0.01, 0.1],
             'n_estimators': [300]
             }
scoring = {'accuracy', 'precision', 'recall', 'f1'}
xgb_cv = GridSearchCV(xgb, cv_params, scoring=scoring, cv=4, refit='recall')
```

In [ ]:
```
# Fitting the data
xgb_cv.fit(X_train, y_train)
```

Out[ ]:
```
GridSearchCV(cv=4, error_score=nan,
             estimator=XGBClassifier(base_score=None, booster=None,
                                     callbacks=None, colsample_bylevel=None,
                                     colsample_bynode=None,
                                     colsample_bytree=None,
                                     early_stopping_rounds=None,
                                     enable_categorical=False, eval_metric=None,
                                     gamma=None, gpu_id=None, grow_policy=None,
                                     importance_type=None,
                                     interaction_constraints=None,
                                     learning_rate=None, max...
                                     num_parallel_tree=None,
                                     objective='binary:logistic',
                                     predictor=None, random_state=42,
                                     reg_alpha=None, ...),
             iid='deprecated', n_jobs=None,
             param_grid={'learning_rate': [0.01, 0.1], 'max_depth': [6, 12],
                         'min_child_weight': [3, 5], 'n_estimators': [300]},
             pre_dispatch='2*n_jobs', refit='recall', return_train_score=False,
             scoring={'precision', 'f1', 'accuracy', 'recall'}, verbose=0)
```

In [ ]:
```
# Best score
xgb_cv.best_score_
```

Out[ ]:
```
0.9408019426676142
```

In [ ]:
```
# Best parameters
xgb_cv.best_params_
```

Out[ ]:
```
{'learning_rate': 0.1,
 'max_depth': 12,
 'min_child_weight': 3,
 'n_estimators': 300}
```

In [ ]:
```
# Model validation
xgb_val_prediction = xgb_cv.best_estimator_.predict(X_val)
xgb_val_prediction
```

Out[ ]:
```
array([0, 0, 1, ..., 0, 1, 0])
```

In [ ]:
```
# Scores helper function
def get_test_scores(model_name:str, preds, y_test_data):
    '''
    Generate a table of test scores.

    In:
        model_name (string): Your choice: how the model will be named in the output
        preds: numpy array of test predictions
        y_test_data: numpy array of y_test data

    Out:
        table: a pandas df of precision, recall, f1, and accuracy scores for your m
    '''
    accuracy = accuracy_score(y_test_data, preds)
    precision = precision_score(y_test_data, preds)
```

```
    recall = recall_score(y_test_data, preds)
    f1 = f1_score(y_test_data, preds)

    table = pd.DataFrame({'model': [model_name],
                          'precision': [precision],
                          'recall': [recall],
                          'F1': [f1],
                          'accuracy': [accuracy]
                          })

    return table
```

In [ ]:

```
# Evaluate model scores
xgb_scores = get_test_scores('XGB val', xgb_val_prediction, y_val)
xgb_scores
```

Out[ ]:

	model	precision	recall	F1	accuracy
0	XGB val	0.973554	0.9424	0.957724	0.98019

In [ ]:

```
# Test data predictions
xgb_test_prediction = xgb_cv.best_estimator_.predict(X_test)
xgb_test_scores = get_test_scores('XGB test', xgb_test_prediction, y_test)
xgb_test_scores
```

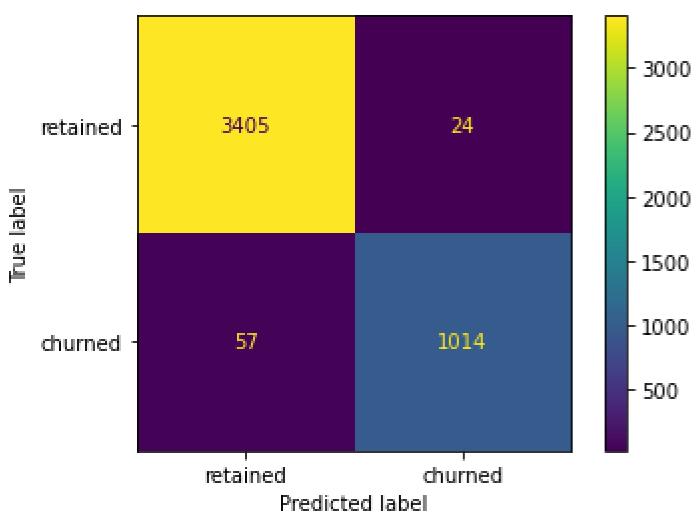
Out[ ]:

	model	precision	recall	F1	accuracy
0	XGB test	0.976879	0.946779	0.961593	0.982

In [ ]:

```
# Confusion matrix
cm = confusion_matrix(y_test, xgb_test_prediction, labels=xgb_cv.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['retained', 'chu
disp.plot(values_format='')
```

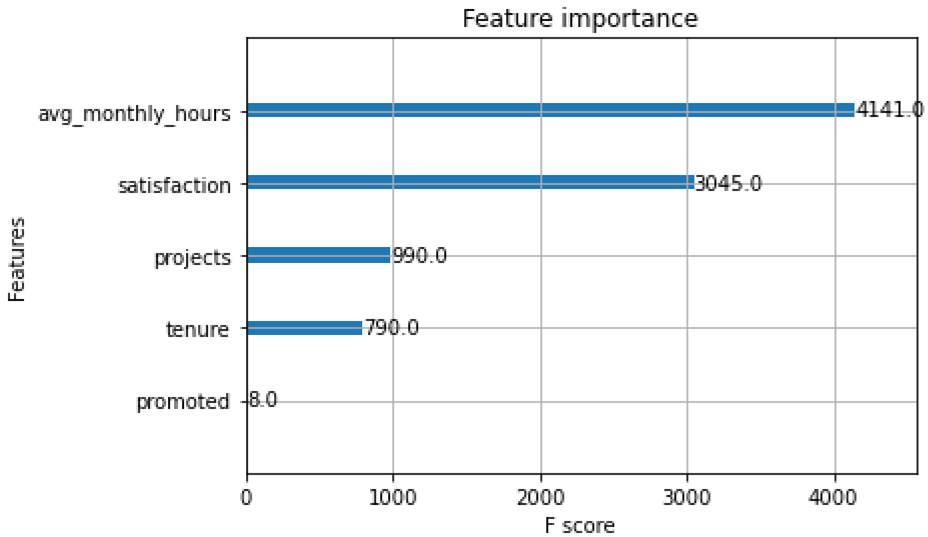
Out[ ]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fb0f4ef7d90>



In [ ]:

```
plot_importance(xgb_cv.best_estimator_)
```

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb0f4e8fc50>



Summary of model results

- Using the provided observations, a model with accuracy of 96% was constructed.
- The model shows minimal False Positive and False Negative results.

Conclusion, Recommendations, Next Steps

- With high confidence, one of the most important contributors to churn for the company is "working hours" and "number of projects".
- This indicates that workload is distributed in an unfavorable way, with strong correlation between identified contributors and churn increase.
- Salifort Motors can take steps to remedy the issue by distributing tasks in an advantageous way.