EmployeeAttrition

April 18, 2019

```
In [1]: import numpy as np
        import pandas as pd
        import seaborn as sns
        import matplotlib.pyplot as plt
        import matplotlib.colors
        import scipy.stats
        import sklearn.decomposition.pca
        import sklearn.cluster
        import sklearn.model_selection
        import sklearn.ensemble
        import sklearn.metrics
```

1 Employee Attrition

1.1 Loading data

```
In [2]: # Load data
        employees = pd.read_csv("hr_attrition_train.csv", index_col=0)
        employees.head()
```

```
Out[2]:    satisfaction_level  last_evaluation  number_project  average_montly_hours  \
        id
        1                0.38             0.53               2                   157
        2                0.80             0.86               5                   262
        3                0.11             0.88               7                   272
        4                0.72             0.87               5                   223
        5                0.37             0.52               2                   159

            time_spend_company  Work_accident  left  promotion_last_5years  sales  \
        id
        1                    3              0     1                      0  sales
        2                    6              0     1                      0  sales
        3                    4              0     1                      0  sales
        4                    5              0     1                      0  sales
        5                    3              0     1                      0  sales

            salary
```

```
id
1       low
2    medium
3    medium
4       low
5       low
```

```
In [3]: employees.describe(include='all')
```

Out[3]:

	satisfaction_level	last_evaluation	number_project
count	13000.000000	13000.000000	13000.000000
unique	NaN	NaN	NaN
top	NaN	NaN	NaN
freq	NaN	NaN	NaN
mean	0.618806	0.716709	3.804077
std	0.246630	0.170237	1.209814
min	0.090000	0.360000	2.000000
25%	0.450000	0.560000	3.000000
50%	0.650000	0.720000	4.000000
75%	0.820000	0.870000	5.000000
max	1.000000	1.000000	7.000000

	average_montly_hours	time_spend_company	Work_accident	left
count	13000.000000	13000.000000	13000.000000	13000.000000
unique	NaN	NaN	NaN	NaN
top	NaN	NaN	NaN	NaN
freq	NaN	NaN	NaN	NaN
mean	200.909769	3.390000	0.147077	0.214077
std	49.484224	1.312204	0.354196	0.410196
min	96.000000	2.000000	0.000000	0.000000
25%	156.000000	3.000000	0.000000	0.000000
50%	200.000000	3.000000	0.000000	0.000000
75%	244.000000	4.000000	0.000000	0.000000
max	310.000000	10.000000	1.000000	1.000000

	promotion_last_5years	sales	salary
count	13000.000000	13000	13000
unique	NaN	10	3
top	NaN	sales	low
freq	NaN	3536	6312
mean	0.016462	NaN	NaN
std	0.127247	NaN	NaN
min	0.000000	NaN	NaN
25%	0.000000	NaN	NaN
50%	0.000000	NaN	NaN
75%	0.000000	NaN	NaN
max	1.000000	NaN	NaN

The first 5 features are numerical in nature but the remaining 5 are categorical.

“Work_accident” is described as a numerical feature in the metadata but because it can only take on values of 0 and 1 (see min/max above and the number of unique values below), it may as well be treated as a boolean.

```
In [4]: employees.nunique()
```

```
Out[4]: satisfaction_level        92
        last_evaluation           65
        number_project             6
        average_montly_hours     215
        time_spend_company         8
        Work_accident              2
        left                       2
        promotion_last_5years      2
        sales                     10
        salary                     3
        dtype: int64
```

1.1.1 Fixing column names and editing binary features

There are some typos in the column names that I want to fix in the code here for the sake of consistency and so that I don’t keep making typos further down in the code. I am leaving the data itself untouched so that the code is compatible with different versions of the data.

Furthermore, the features “left”, and “promotion_last_5years” are converted to boolean as they are binary flags.

```
In [5]: def change_column_names_and_boolean_features(df):
            df.rename(
                columns={
                    "number_project": "number_projects",
                    "average_montly_hours": "average_monthly_hours",
                    "time_spend_company": "time_spent_company",
                    "Work_accident": "num_work_accidents",
                    "sales": "department"},
                inplace=True)

            if "left" in df.keys():
                df["left"] = df["left"].astype(bool)
            df["promotion_last_5years"] = df["promotion_last_5years"].astype(bool)

        change_column_names_and_boolean_features(employees)
        employees.head()
```

```
Out[5]:     satisfaction_level  last_evaluation  number_projects  \
        id
        1                 0.38             0.53                2
        2                 0.80             0.86                5
        3                 0.11             0.88                7
        4                 0.72             0.87                5
```

```
5                 0.37             0.52                2

    average_monthly_hours  time_spent_company  num_work_accidents  left  \
id
1                     157                   3                   0  True
2                     262                   6                   0  True
3                     272                   4                   0  True
4                     223                   5                   0  True
5                     159                   3                   0  True

    promotion_last_5years department  salary
id
1                   False      sales     low
2                   False      sales  medium
3                   False      sales  medium
4                   False      sales     low
5                   False      sales     low
```

1.1.2 Data quality

There are no null values in the dataset, so no further cleaning is required.

In [6]:
```
employees.isnull().any()
```

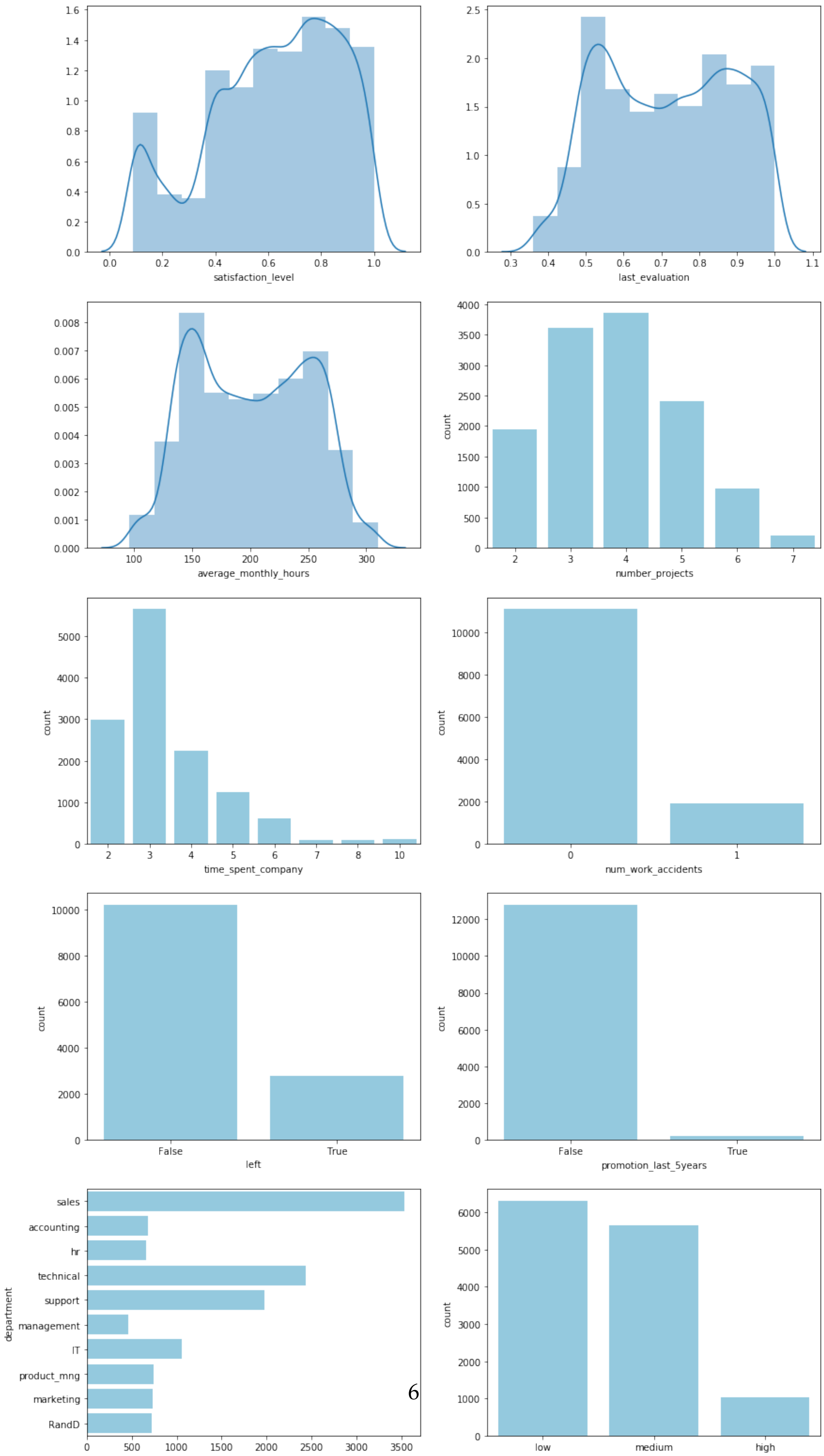
Out[6]:
```
satisfaction_level       False
last_evaluation          False
number_projects          False
average_monthly_hours    False
time_spent_company       False
num_work_accidents       False
left                     False
promotion_last_5years    False
department               False
salary                   False
dtype: bool
```

1.2 Feature distributions

- There appears to be a bimodal trend that splits employees into two, strongly overlapping groups based on the satisfaction levels, evaluation scores, and average monthly working hours.
- The number of projects and time spent at the company appear to be poisson distributed

In [7]:
```
fig, ax = plt.subplots(5, 2, figsize=(14, 28));
sns.distplot(employees["satisfaction_level"], bins=10, ax=ax[0, 0]);
sns.distplot(employees["last_evaluation"], bins=10, ax=ax[0, 1]);
sns.distplot(employees["average_monthly_hours"], bins=10, ax=ax[1, 0]);
sns.countplot(employees["number_projects"], color="skyblue", ax=ax[1, 1]);
sns.countplot(employees["time_spent_company"], color="skyblue", ax=ax[2, 0]);
```

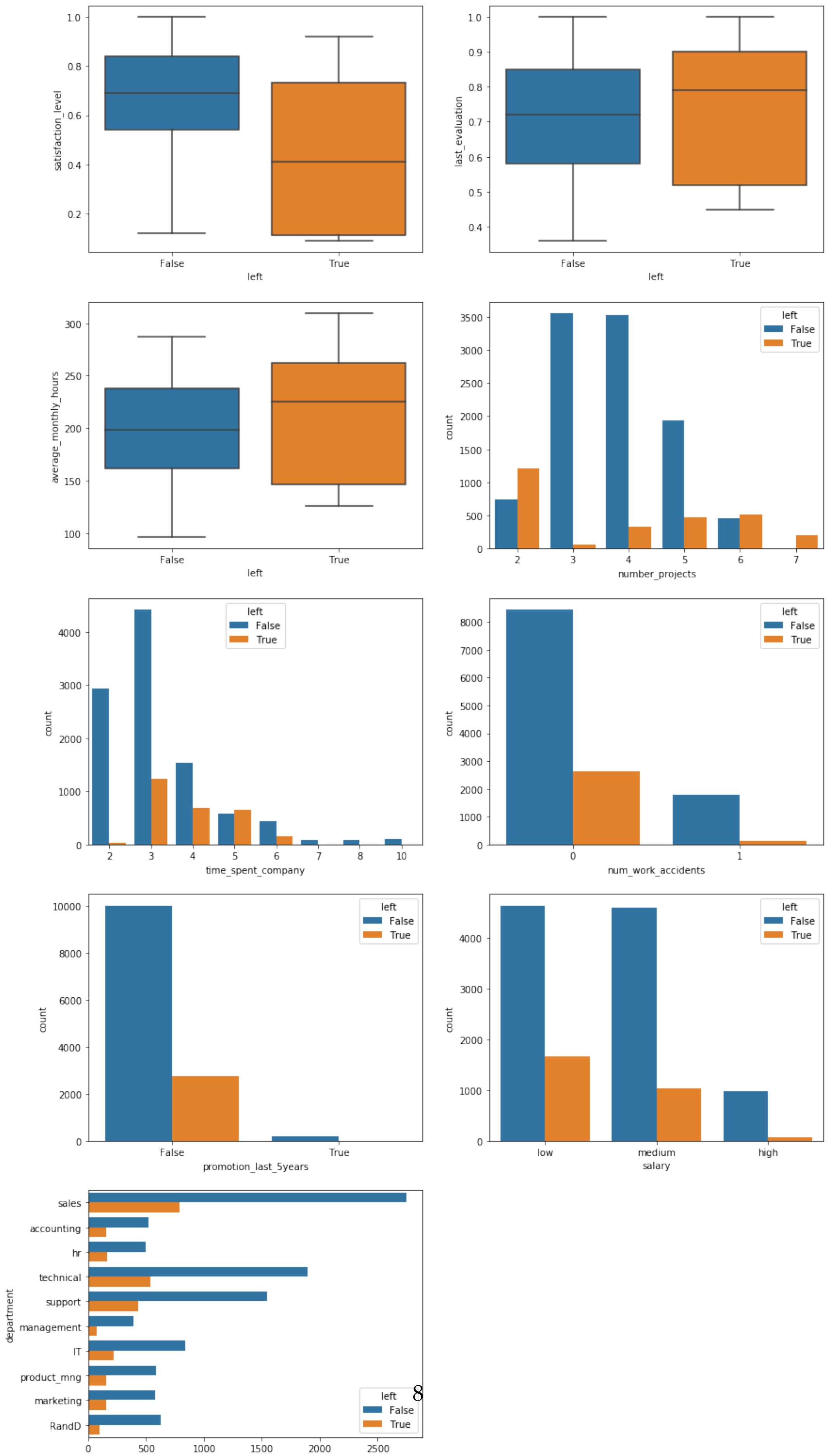
```
sns.countplot(employees["num_work_accidents"], color="skyblue", ax=ax[2, 1]);
sns.countplot(employees["left"], color="skyblue", ax=ax[3, 0]);
sns.countplot(employees["promotion_last_5years"], color="skyblue", ax=ax[3, 1]);
sns.countplot(y=employees["department"], color="skyblue", ax=ax[4, 0]);
sns.countplot(employees["salary"], color="skyblue", ax=ax[4, 1]);
```


satisfaction_level
last_evaluation
average_monthly_hours
number_projects
count
time_spent_company
count
num_work_accidents
count
False
True
left
count
False
True
promotion_last_5years
sales
accounting
hr
technical
support
management
IT
product_mng
marketing
RandD
department
count
low
medium
high
salary
count

1.3 Individual feature relationships

If we split employees into two groups, those who have left and those who haven't, then the first step is to look at how individual features vary between these groups independently.

```
In [8]: fig, ax = plt.subplots(5, 2, figsize=(14, 28));
        sns.boxplot(data=employees, x="left", y="satisfaction_level", ax=ax[0, 0]);
        sns.boxplot(data=employees, x="left", y="last_evaluation", ax=ax[0, 1]);
        sns.boxplot(data=employees, x="left", y="average_monthly_hours", ax=ax[1, 0]);
        sns.countplot(data=employees, x="number_projects", hue="left", ax=ax[1, 1]);
        sns.countplot(data=employees, x="time_spent_company", hue="left", ax=ax[2, 0]);
        sns.countplot(data=employees, x="num_work_accidents", hue="left", ax=ax[2, 1]);
        sns.countplot(data=employees, x="promotion_last_5years", hue="left", ax=ax[3, 0]);
        sns.countplot(data=employees, y="department", hue="left", ax=ax[4, 0]);
        sns.countplot(data=employees, x="salary", hue="left", ax=ax[3, 1]);
        ax[4, 1].axis("off");
```


satisfaction_level
1.0
0.8
0.6
0.4
0.2
False
True
left
last_evaluation
1.0
0.9
0.8
0.7
0.6
0.5
0.4
False
True
left
average_monthly_hours
300
250
200
150
100
False
True
left
count
3500
3000
2500
2000
1500
1000
500
0
2
3
4
5
6
7
number_projects
left
False
True
count
4000
3000
2000
1000
0
2
3
4
5
6
7
8
10
time_spent_company
left
False
True
count
8000
7000
6000
5000
4000
3000
2000
1000
0
0
1
num_work_accidents
left
False
True
count
10000
8000
6000
4000
2000
0
False
True
promotion_last_5years
left
False
True
count
4000
3000
2000
1000
0
low
medium
high
salary
left
False
True
department
sales
accounting
hr
technical
support
management
IT
product_mng
marketing
RandD
0
500
1000
1500
2000
2500
count
left
False
True

Several initial hypotheses can be formed from these visuals:

- As expected, satisfaction level plays an important role in whether an employee leaves the company.
- Employees with both a large **and** small number of projects, i.e. over- and underworked employees, are more likely to leave. The employees that stay at the company occupy a "golden middle" in terms of workload.
- The vast majority of leaving employees only do so after at least 3 years at the company. However, once an employee stays for a very long time, at least 6 years, they appear to remain loyal to the company.

Of particular note is that every single employee with 7 projects left the company. This is a total of 202 employees.

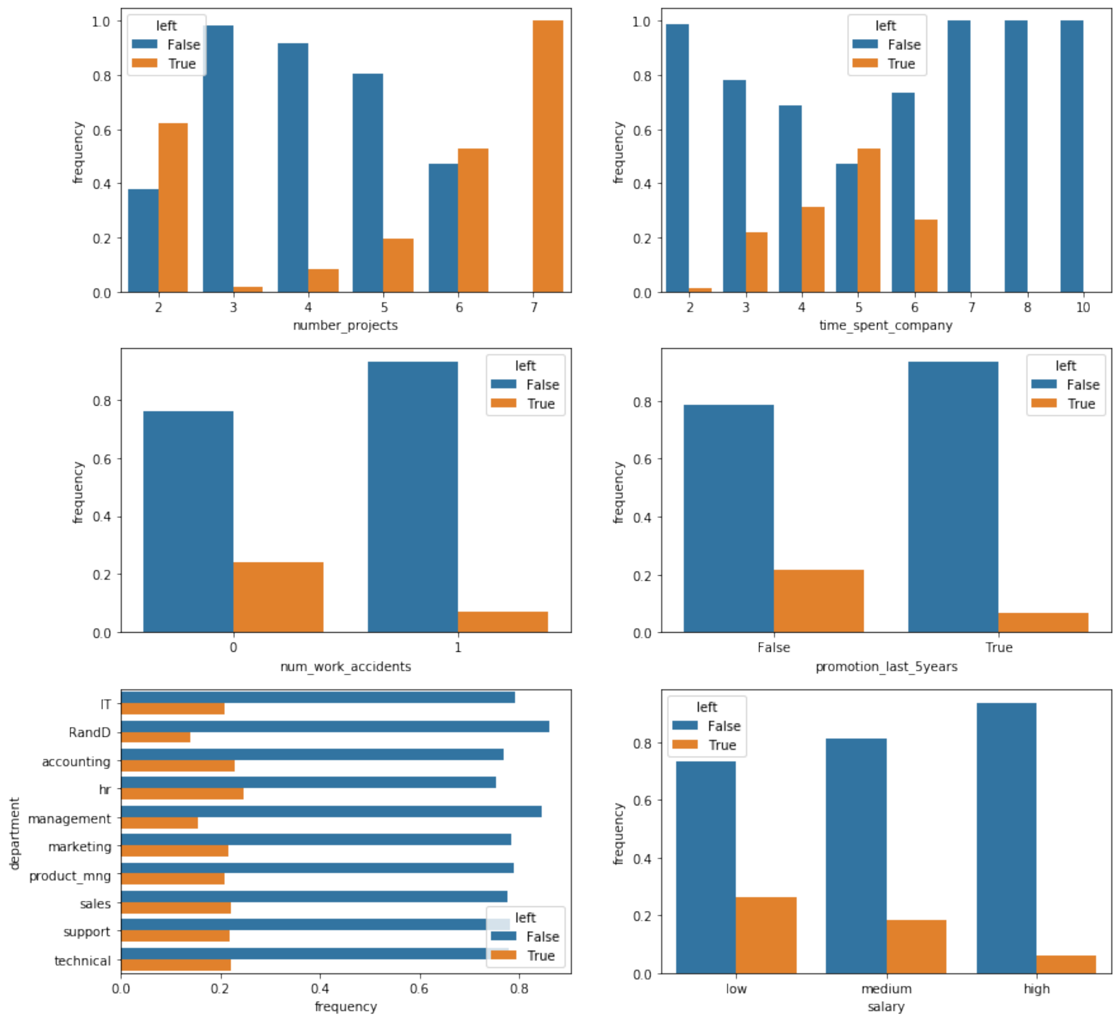
```
In [9]: (employees["number_projects"] == 7).sum()
```

```
Out[9]: 202
```

The barplots can also be normalized to show relative frequencies rather than absolute counts. This lets us ignore the class imbalance since the majority of employees in the dataset did not leave the company.

```
In [10]: fig, ax = plt.subplots(3, 2, figsize=(14, 14));
         sns.barplot(
             data=employees.groupby(["number_projects", "left"]).size().unstack().apply(
                 lambda x: x/x.sum(), axis=1).reset_index().melt(
                 id_vars="number_projects", value_name="frequency"),
             x="number_projects", y="frequency", hue="left", ax=ax[0, 0]);
         sns.barplot(
             data=employees.groupby(["time_spent_company", "left"]).size().unstack().apply(
                 lambda x: x/x.sum(), axis=1).reset_index().melt(
                 id_vars="time_spent_company", value_name="frequency"),
             x="time_spent_company", y="frequency", hue="left", ax=ax[0, 1]);
         sns.barplot(
             data=employees.groupby(["num_work_accidents", "left"]).size().unstack().apply(
                 lambda x: x/x.sum(), axis=1).reset_index().melt(
                 id_vars="num_work_accidents", value_name="frequency"),
             x="num_work_accidents", y="frequency", hue="left", ax=ax[1, 0]);
         sns.barplot(
             data=employees.groupby(["promotion_last_5years", "left"]).size().unstack().apply(
                 lambda x: x/x.sum(), axis=1).reset_index().melt(
                 id_vars="promotion_last_5years", value_name="frequency"),
             x="promotion_last_5years", y="frequency", hue="left", ax=ax[1, 1]);
         sns.barplot(
             data=employees.groupby(["department", "left"]).size().unstack().apply(
                 lambda x: x/x.sum(), axis=1).reset_index().melt(
                 id_vars="department", value_name="frequency"),
```

```
    y="department", x="frequency", hue="left", ax=ax[2, 0]);
sns.barplot(
    data=employees.groupby(["salary", "left"]).size().unstack().apply(
        lambda x: x/x.sum(), axis=1).reset_index().melt(
        id_vars="salary", value_name="frequency"),
    x="salary", y="frequency", hue="left", ax=ax[2, 1],
    order=["low", "medium", "high"]);
```



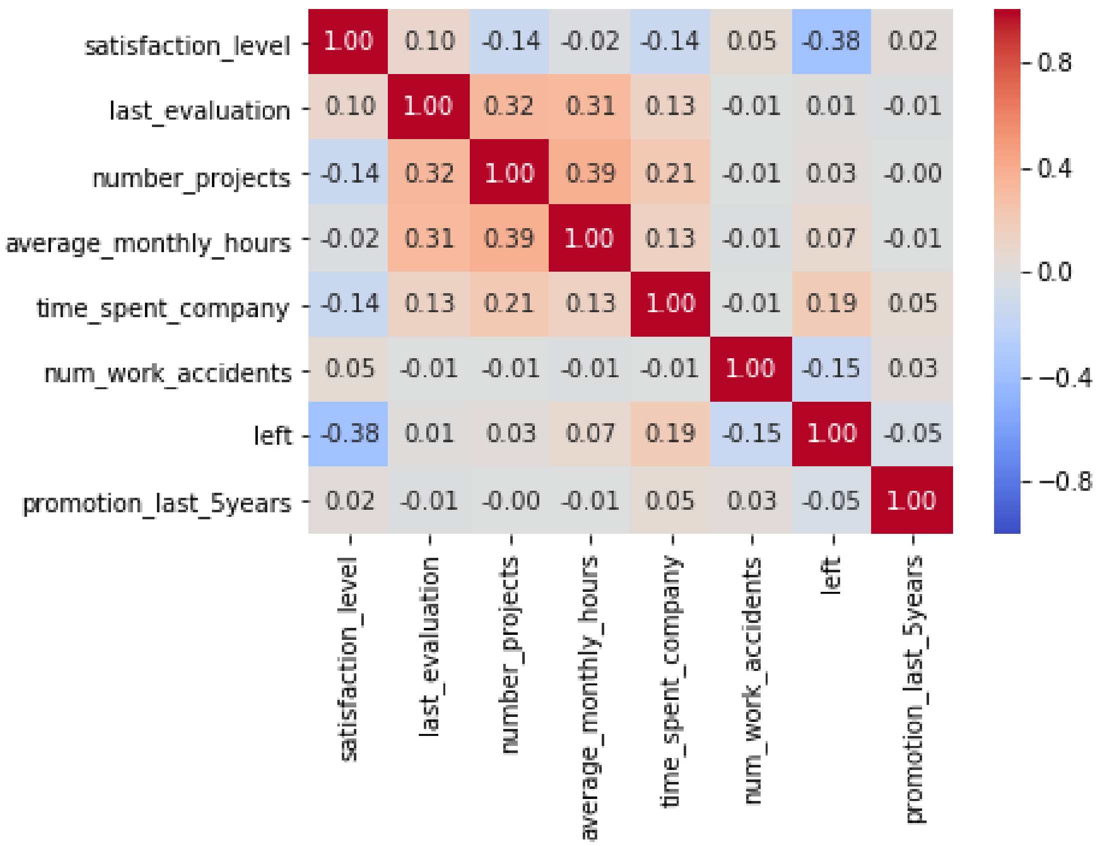
From the normalized barplots we can see the following: - Work accidents, surprisingly, *decrease* the probability of an employee leaving the company. It is worth noting that there may be an inherent bias in this assertion as the dataset most likely does not include employees who became unable to work due to an accident. - Receiving a promotion within the last 5 years, unsurprisingly, also decreases that probability. - Management and R&D employees are slightly less likely to leave but for the most part, the department an employee works in seems to have an insignificant impact on their likelihood of leaving. - The probability of leaving is, unsurprisingly, inversely proportional to an employee's salary.

1.4 Correlations

There are weak correlations between features, in particular the number of projects, the average number of hours worked, and the last evaluation score show minor correlation. These correlation coefficients are not high enough, however, to warrant immediate concern.

```
In [11]: sns.heatmap(
             employees.corr(), cmap="coolwarm",
             vmin=-1, vmax=1, annot=True, fmt=".2f")
```

```
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe02c470940>
```



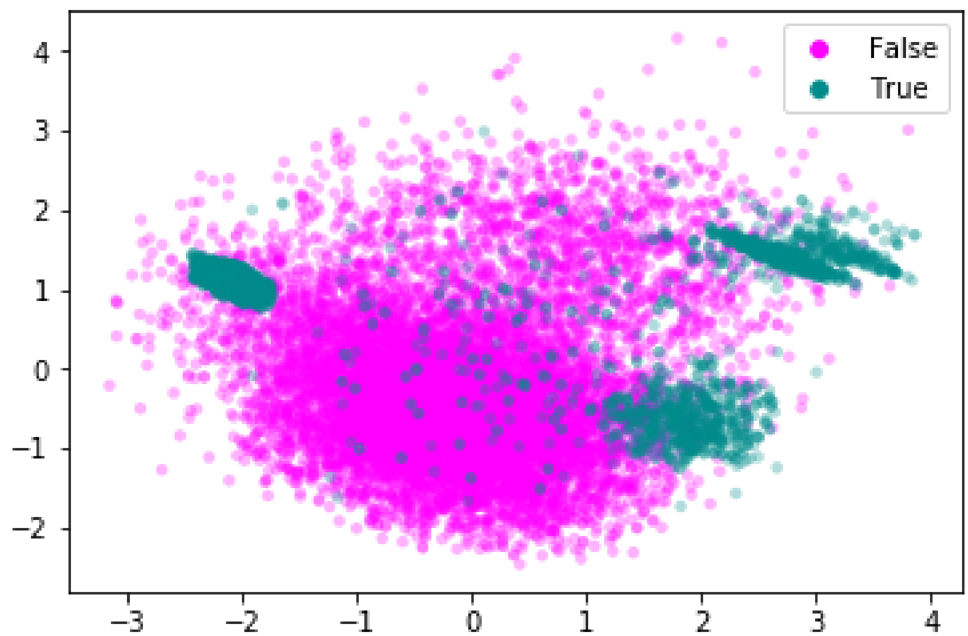
1.5 Clustering

Clustering data with mixed continuous and categorical variables is always tricky. Nonetheless, if we look at a principal component analysis with 2 components of the continuous variables then we notice that there appear to be three main groups of employees who leave the company.

```
In [12]: pca = sklearn.decomposition.pca.PCA(n_components=2).fit_transform(
             employees.drop(
             ["num_work_accidents", "left",
```

```
     "promotion_last_5years", "department", "salary"],
    axis=1).apply(lambda x: (x - x.mean()) / x.std()))

fig, ax = plt.subplots();
for val, color in [(False, "magenta"), (True, "darkcyan")]:
    ax.scatter(
        pca[employees["left"].values == val, 0],
        pca[employees["left"].values == val, 1],
        c=color, label=val, alpha=0.3, edgecolors="none", s=20);
l = plt.legend()
l.legendHandles[0].set_alpha(1)
l.legendHandles[1].set_alpha(1)
l.legendHandles[0].set_sizes((50,))
l.legendHandles[1].set_sizes((50,))
```

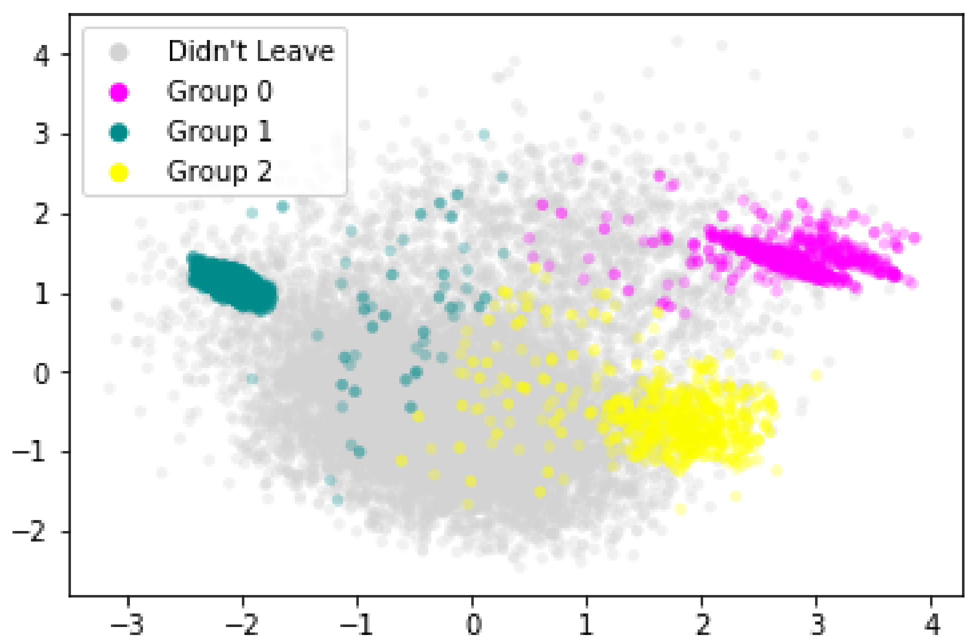


Let's attempt to cluster these three groups.

```
In [13]: # The random_state value makes sure that my descriptions in the text are
         # consistent with the class labels.
         cluster = sklearn.cluster.KMeans(n_clusters=3, random_state=991).fit_predict(
             pca[employees["left"].values == True, :])

         fig, ax = plt.subplots();
         ax.scatter(
             pca[employees["left"].values == False, 0],
             pca[employees["left"].values == False, 1],
             c="lightgray", label="Didn't Leave", alpha=0.3,
```

```
    edgecolors="none", s=20);
for val, color in [(0, "magenta"), (1, "darkcyan"), (2, "yellow")]:
    pca_leavers = pca[employees["left"].values == True, :]
    ax.scatter(
        pca_leavers[cluster == val, 0],
        pca_leavers[cluster == val, 1],
        c=color, label="Group {}".format(val), alpha=0.3,
        edgecolors="none", s=20);
l = plt.legend()
l.legendHandles[0].set_alpha(1)
l.legendHandles[1].set_alpha(1)
l.legendHandles[2].set_alpha(1)
l.legendHandles[3].set_alpha(1)
l.legendHandles[0].set_sizes((50,))
l.legendHandles[1].set_sizes((50,))
l.legendHandles[2].set_sizes((50,))
l.legendHandles[3].set_sizes((50,))
```

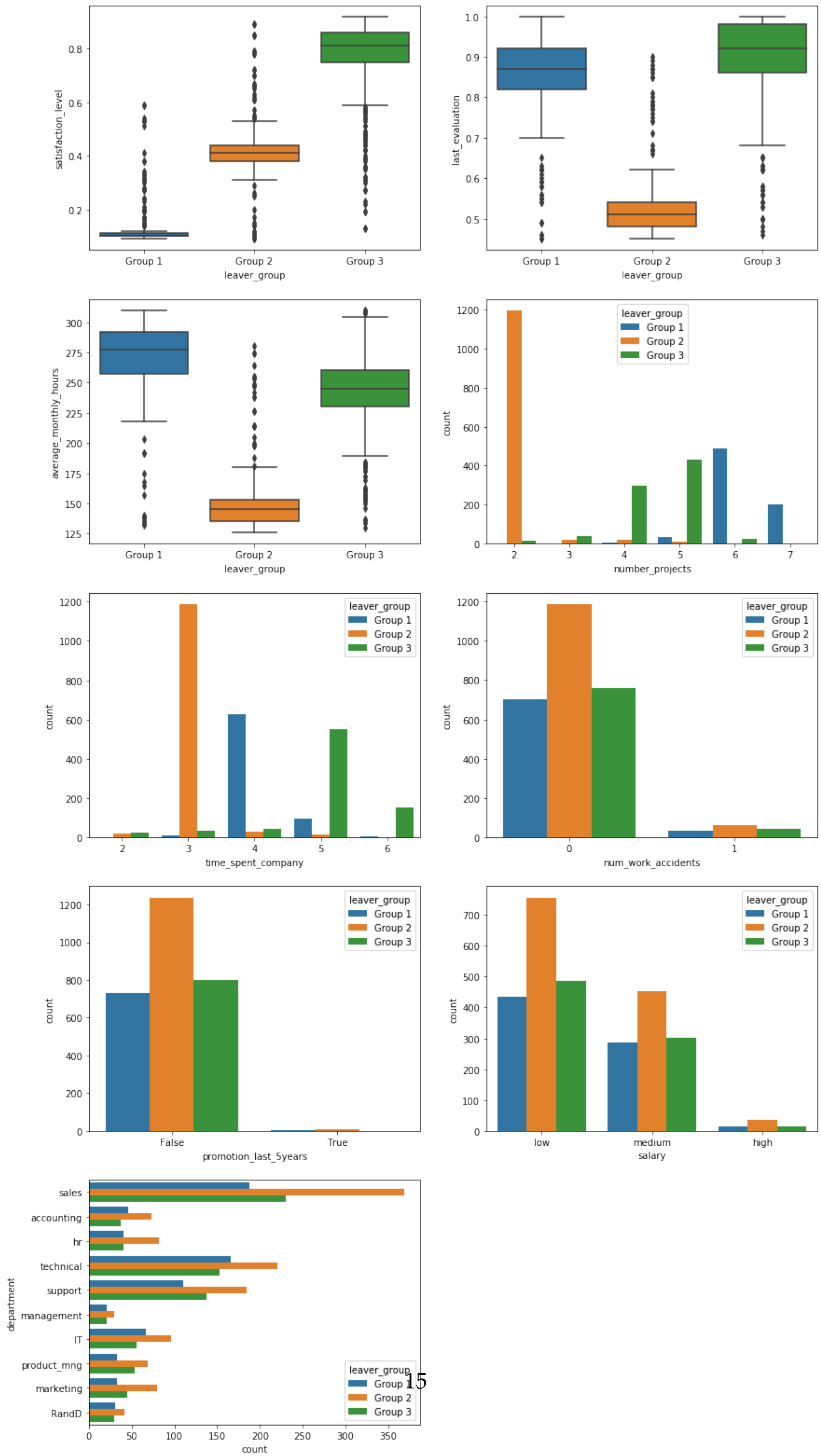


Let's now look at the distribution of features for each of these subgroups individually.

```
In [14]: leavers = employees.loc[employees["left"] == True, :].copy()
         leavers["leaver_group"] = ["Group {}".format(ii+1) for ii in cluster]

         fig, ax = plt.subplots(5, 2, figsize=(14, 28));
         sns.boxplot(data=leavers, x="leaver_group", y="satisfaction_level",
                     order=["Group 1", "Group 2", "Group 3"], ax=ax[0, 0]);
         sns.boxplot(data=leavers, x="leaver_group", y="last_evaluation",
```

```
             order=["Group 1", "Group 2", "Group 3"], ax=ax[0, 1]);
sns.boxplot(data=leavers, x="leaver_group", y="average_monthly_hours",
             order=["Group 1", "Group 2", "Group 3"], ax=ax[1, 0]);
sns.countplot(data=leavers, hue="leaver_group", x="number_projects",
              hue_order=["Group 1", "Group 2", "Group 3"], ax=ax[1, 1]);
sns.countplot(data=leavers, hue="leaver_group", x="time_spent_company",
              hue_order=["Group 1", "Group 2", "Group 3"], ax=ax[2, 0]);
sns.countplot(data=leavers, hue="leaver_group", x="num_work_accidents",
              hue_order=["Group 1", "Group 2", "Group 3"], ax=ax[2, 1]);
sns.countplot(data=leavers, hue="leaver_group", x="promotion_last_5years",
              hue_order=["Group 1", "Group 2", "Group 3"], ax=ax[3, 0]);
sns.countplot(data=leavers, hue="leaver_group", y="department",
              hue_order=["Group 1", "Group 2", "Group 3"], ax=ax[4, 0]);
sns.countplot(data=leavers, hue="leaver_group", x="salary",
              hue_order=["Group 1", "Group 2", "Group 3"], ax=ax[3, 1]);
ax[4, 1].axis("off");
```


satisfaction_level
0.2
0.4
0.6
0.8
Group 1
Group 2
Group 3
leaver_group
last_evaluation
0.5
0.6
0.7
0.8
0.9
1.0
Group 1
Group 2
Group 3
leaver_group
average_monthly_hours
125
150
175
200
225
250
275
300
Group 1
Group 2
Group 3
leaver_group
count
0
200
400
600
800
1000
1200
2
3
4
5
6
7
number_projects
leaver_group
Group 1
Group 2
Group 3
count
0
200
400
600
800
1000
1200
2
3
4
5
6
time_spent_company
leaver_group
Group 1
Group 2
Group 3
count
0
200
400
600
800
1000
1200
0
1
num_work_accidents
leaver_group
Group 1
Group 2
Group 3
count
0
200
400
600
800
1000
1200
False
True
promotion_last_5years
leaver_group
Group 1
Group 2
Group 3
count
0
100
200
300
400
500
600
700
low
medium
high
salary
leaver_group
Group 1
Group 2
Group 3
department
sales
accounting
hr
technical
support
management
IT
product_mng
marketing
RandD
0
50
100
150
200
250
300
350
count
leaver_group
Group 1
Group 2
Group 3

This stratification paints an interesting picture and lets us make the following hypotheses: - Employees in group 1 are overworked. They work the longest hours, have the highest number of projects (all of the employees with 7 projects appear to be in this group), and are extremely dissatisfied because of it. Nonetheless, they are evaluated very highly, meaning they most likely leave of their own volition to improve their work-life balance. - Group 2 consists of employees who are underworked and evaluated poorly for it. Almost all of them stayed with the company for 3 years but only worked on 2 projects. Their average monthly working hours are notably lower than the other two groups. The most likely explanation is that these employees are either asked to leave by their employer or are fundamentally unhappy with and/or unsuited for their job. - Group 3 is a curious group. They are very satisfied, scored high on their last evaluation, and appear to be in the "golden middle" with regards to the number of projects. They tend to stay with the company longer than the other two groups of leavers. These employees may have difficulty moving into senior positions within the company due to internal competition and therefore leave to advance their careers. Retirees may also fall into this group.

The categorical variables show no distinction between the groups but this is unsurprising as they were not used in the clustering.

1.6 Predicting attrition

In order to more precisely predict employee attrition, we turn towards machine learning models that can identify more complex relationships between features.

1.6.1 Converting categorical features

The first step is to convert categorical features into numerical, one-hot features. Specifically, the department and salary must be converted. The number of work accidents and the promotion status are boolean and can be used as-is.

```
In [15]: employees_dummy = pd.get_dummies(employees)
         employees_dummy["leaver_group"] = employees_dummy["left"].copy()
         employees_dummy.loc[employees_dummy["leaver_group"] == True,
                             "leaver_group"] = leavers["leaver_group"]
         employees_dummy.loc[employees_dummy["leaver_group"] == False,
                             "leaver_group"] = "Didn't leave"
         employees_dummy.head()
```

```
Out[15]:     satisfaction_level  last_evaluation  number_projects  \
         id
         1                 0.38             0.53                2
         2                 0.80             0.86                5
         3                 0.11             0.88                7
         4                 0.72             0.87                5
         5                 0.37             0.52                2

             average_monthly_hours  time_spent_company  num_work_accidents  left  \
         id
```

```
1                      157                  3                   0  True
2                      262                  6                   0  True
3                      272                  4                   0  True
4                      223                  5                   0  True
5                      159                  3                   0  True

    promotion_last_5years  department_IT  department_RandD  ...  \
id                                                          ...
1                   False              0                 0  ...
2                   False              0                 0  ...
3                   False              0                 0  ...
4                   False              0                 0  ...
5                   False              0                 0  ...

    department_management  department_marketing  department_product_mng  \
id
1                       0                     0                       0
2                       0                     0                       0
3                       0                     0                       0
4                       0                     0                       0
5                       0                     0                       0

    department_sales  department_support  department_technical  salary_high  \
id
1                  1                   0                     0            0
2                  1                   0                     0            0
3                  1                   0                     0            0
4                  1                   0                     0            0
5                  1                   0                     0            0

    salary_low  salary_medium  leaver_group
id
1            1              0       Group 2
2            0              1       Group 3
3            0              1       Group 1
4            1              0       Group 3
5            1              0       Group 2

[5 rows x 22 columns]
```

In [16]:
```
employees_dummy["left"].value_counts()
```

Out[16]:
```
False    10217
True      2783
Name: left, dtype: int64
```

In [17]:
```
employees_dummy["leaver_group"].value_counts()
```

Out[17]:
```
Didn't leave    10217
Group 2          1246
```

```
Group 3          802
Group 1          735
Name: leaver_group, dtype: int64
```

1.6.2 Class imbalance

In general, class imbalance can be handled via up- or downsampling of individual categories. A number of sampling techniques exist and could be explored. However, the number of samples in each category is much larger than the number of features. Therefore, downsampling the larger category still retains a sufficient number of data points to train a model.

```
In [18]: # downsample 'False' group
         x = employees_dummy.groupby("left").apply(
             lambda x: x.sample(n = employees_dummy.groupby("left").size().min()))
         y = x["left"]
         x = x.drop(["left", "leaver_group"], axis=1)
         y.value_counts()

Out[18]: True     2783
         False    2783
         Name: left, dtype: int64

In [19]: x_train, x_test, y_train, y_test = sklearn.model_selection.train_test_split(
             x, y, test_size=0.30)
```

1.6.3 Model selection

I chose a random forest model. The reasons for this are: - The features are very heterogeneous, i.e. `satisfaction_level` and `last_evaluation` are bounded by 0 and 1, `average_monthly_hours` is effectively unbounded, `time_spent_company` and `number_projects` appear poisson distributed, and the remaining features are categorical. Normalizing them to make them compatible with a logistic regression, for example, requires assumptions I don't want to make if I don't have to. - Ensemble methods are typically among the most powerful classification algorithms.

I will tune the number of trees in the forest as well as their maximum depth using 5-fold cross-validation.

```
In [20]: cv = sklearn.model_selection.GridSearchCV(
             estimator=sklearn.ensemble.RandomForestClassifier(),
             param_grid={"max_depth": [3, 5, 10, 25, 50, 75, 100, None],
                         "n_estimators": [5, 10, 25, 50, 75, 100, 150, 200]},
             n_jobs=6, cv=5, return_train_score=False).fit(x_train, y_train)

In [21]: print("Best CV score: {:.4f}".format(cv.best_score_))
         print("Best parameters:")
         print("    max_depth={}".format(cv.best_params_["max_depth"]))
         print("    n_estimators={}".format(cv.best_params_["n_estimators"]))

Best CV score: 0.9689
Best parameters:
```

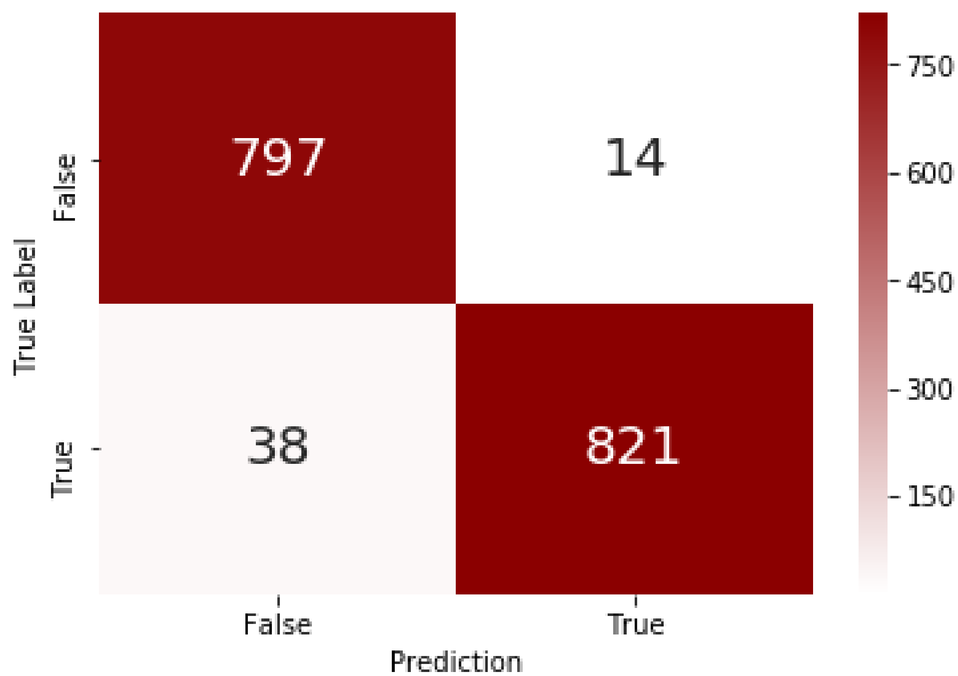
```
max_depth=50
n_estimators=75
```

1.6.4 Training and Evaluation

The most basic metric, and the one that all other metrics build on, is the confusion matrix.

```
In [22]: model = cv.best_estimator_.fit(x_train, y_train)
```

```
In [23]: cm = pd.DataFrame({
             "True Label": y_test.values,
             "Prediction": model.predict(x_test)}).groupby(
             ["True Label", "Prediction"]).size().unstack()
         colormap = matplotlib.colors.LinearSegmentedColormap.from_list(
             "whitered", ["white", "darkred"])
         sns.heatmap(
             cm, annot=True, fmt="d",
             annot_kws={"fontsize": 20}, cmap=colormap);
```



The model has some difficulty with false negatives, i.e. it misses about 5% of employees that leave the company. Objectively, however, the model exhibits adequate accuracy to not require further exploration and fine-tuning of the model, i.e. it's good enough for now.

1.6.5 Feature importance

A look at the feature importances of the model confirm our intuition that satisfaction level, workload (in terms of projects and working hours), time spent at the company, and evaluation scores have the biggest impact on the attrition prediction. Curiously, salary seems much less important than indicated in the EDA above.

```
In [24]: pd.DataFrame({
             "Feature": x_train.columns,
             "Importance": model.feature_importances_}).sort_values(
             "Importance", ascending=False)
```

```
Out[24]:                   Feature  Importance
         0      satisfaction_level    0.261806
         4      time_spent_company    0.231742
         2         number_projects    0.158867
         3    average_monthly_hours   0.144305
         1         last_evaluation    0.144160
         5       num_work_accidents   0.011303
         18              salary_low   0.006678
         17             salary_high   0.006016
         14        department_sales   0.005251
         16    department_technical   0.005025
         19           salary_medium   0.004713
         15      department_support   0.004127
         9    department_accounting   0.002834
         10           department_hr   0.002599
         7            department_IT   0.002407
         8         department_RandD   0.002281
         11   department_management   0.001755
         12    department_marketing   0.001520
         13  department_product_mng   0.001354
         6      promotion_last_5years 0.001259
```

1.6.6 Predicting attrition in test data file

As part of the assessment, I want to apply the model to the test data set.

```
In [25]: # Load data
         employees_test = pd.read_csv("hr_attrition_test.csv", index_col=0)
         change_column_names_and_boolean_features(employees_test)
         employees_test.head()
```

```
Out[25]:        satisfaction_level  last_evaluation  number_projects  \
         id
         13001                0.62             0.94                4
         13002                0.38             0.52                2
         13003                0.80             0.77                4
         13004                0.61             0.42                3
```

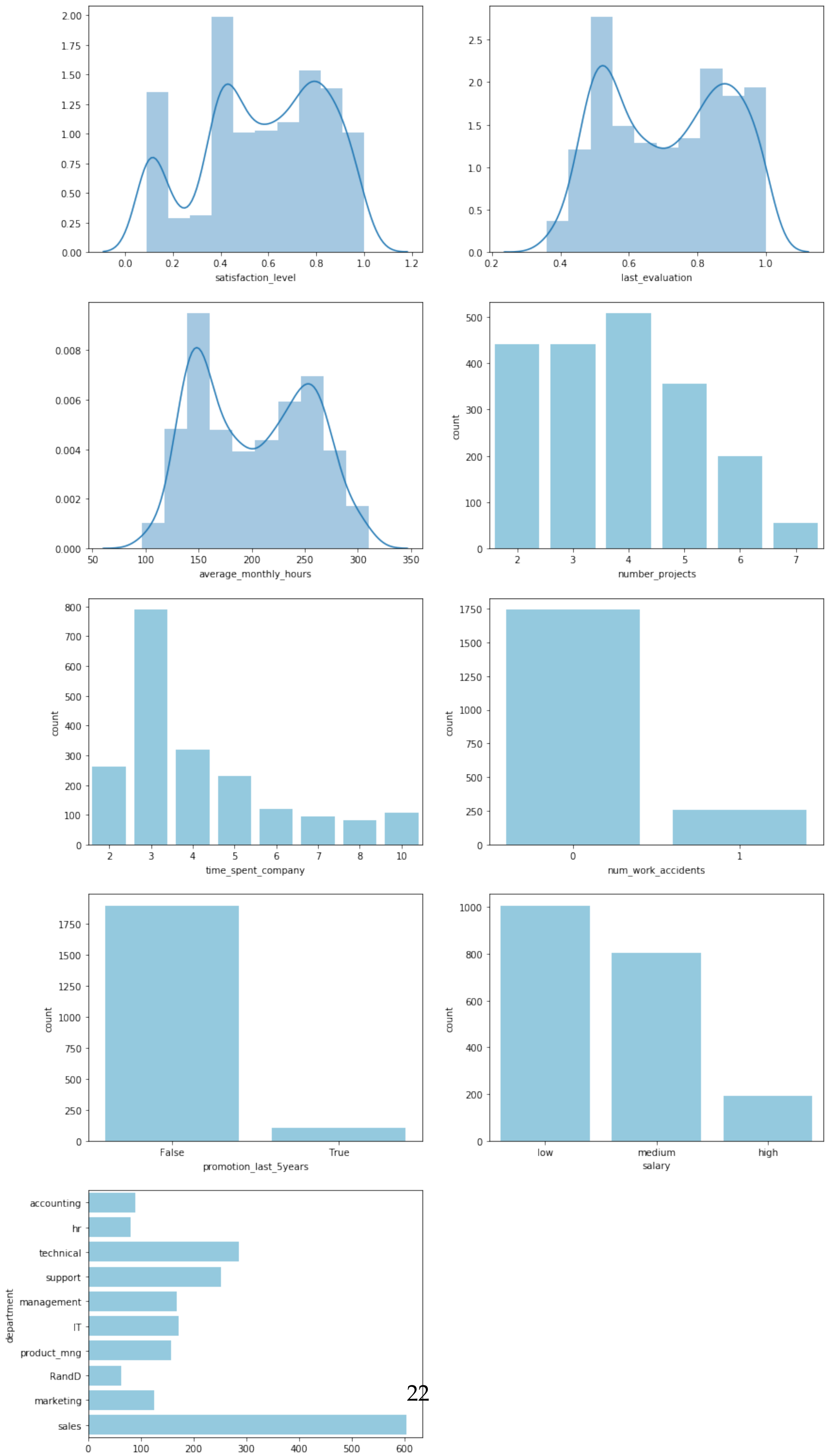
```
13005                0.61            0.56                 4

       average_monthly_hours  time_spent_company  num_work_accidents  \
id
13001                    252                   4                   0
13002                    171                   3                   0
13003                    194                   3                   0
13004                    104                   2                   0
13005                    176                   3                   0

       promotion_last_5years  department  salary
id
13001                  False  accounting     low
13002                  False  accounting  medium
13003                  False  accounting  medium
13004                  False          hr  medium
13005                  False          hr  medium
```

Features are similarly distributed in the test dataset and there are no missing values

In [26]:
```
fig, ax = plt.subplots(5, 2, figsize=(14, 28));
sns.distplot(employees_test["satisfaction_level"], bins=10, ax=ax[0, 0]);
sns.distplot(employees_test["last_evaluation"], bins=10, ax=ax[0, 1]);
sns.distplot(employees_test["average_monthly_hours"], bins=10, ax=ax[1, 0]);
sns.countplot(employees_test["number_projects"], color="skyblue", ax=ax[1, 1]);
sns.countplot(employees_test["time_spent_company"], color="skyblue", ax=ax[2, 0]);
sns.countplot(employees_test["num_work_accidents"], color="skyblue", ax=ax[2, 1]);
sns.countplot(employees_test["promotion_last_5years"], color="skyblue", ax=ax[3, 0]);
sns.countplot(y=employees_test["department"], color="skyblue", ax=ax[4, 0]);
sns.countplot(employees_test["salary"], color="skyblue", ax=ax[3, 1]);
ax[4, 1].axis("off");
```


satisfaction_level
last_evaluation
average_monthly_hours
count
number_projects
count
time_spent_company
count
num_work_accidents
count
False
True
promotion_last_5years
count
low
medium
high
salary
accounting
hr
technical
support
management
IT
product_mng
RandD
marketing
sales
department
count

```
In [27]: employees_test.isnull().any()
```

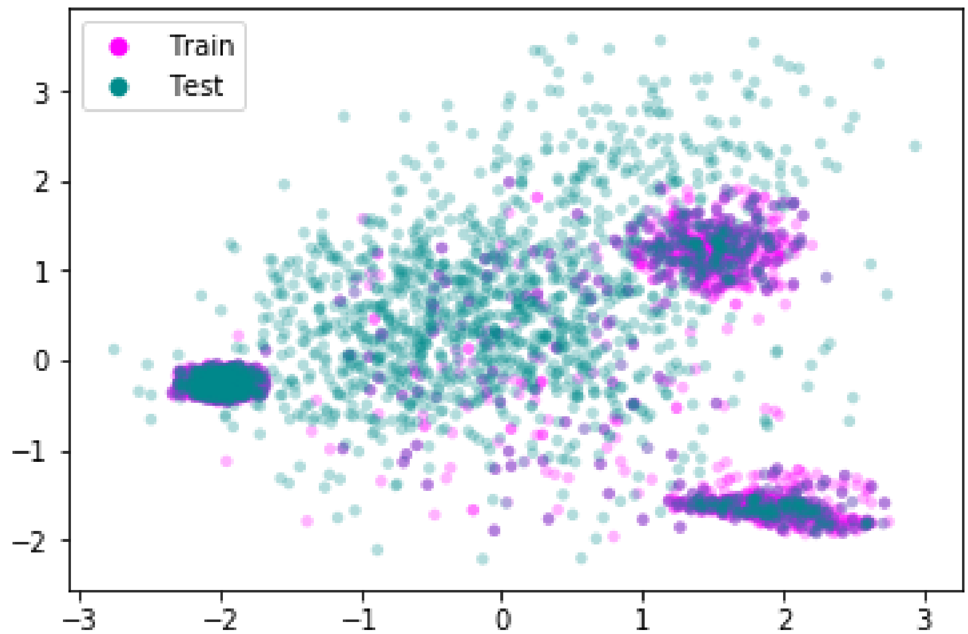
```
Out[27]: satisfaction_level       False
         last_evaluation          False
         number_projects          False
         average_monthly_hours    False
         time_spent_company       False
         num_work_accidents       False
         promotion_last_5years    False
         department               False
         salary                   False
         dtype: bool
```

Performing a PCA-style clustering with the continuous variables shows that the test data set overlaps strongly with one of the leaver groups identified earlier. We can safely assume that the test data stems from the same distribution as the training data and the model should be applicable to it.

```
In [28]: tmp = pd.concat((leavers.drop(["left", "leaver_group"], axis=1), employees_test))
         tmp["traintest"] = "Train"
         tmp.loc[13001:, "traintest"] = "Test"

         pca = sklearn.decomposition.pca.PCA(n_components=2).fit_transform(
             tmp.drop(
             ["num_work_accidents", "promotion_last_5years",
              "department", "salary", "traintest"],
             axis=1).apply(lambda x: (x - x.mean()) / x.std()))

         fig, ax = plt.subplots();
         for val, color in [("Train", "magenta"), ("Test", "darkcyan")]:
             ax.scatter(
                 pca[tmp["traintest"].values == val, 0],
                 pca[tmp["traintest"].values == val, 1],
                 c=color, label=val, alpha=0.3, edgecolors="none", s=20);
         l = plt.legend()
         l.legendHandles[0].set_alpha(1)
         l.legendHandles[1].set_alpha(1)
         l.legendHandles[0].set_sizes((50,))
         l.legendHandles[1].set_sizes((50,))
```



Convert categorical features

```
In [29]: employees_test_dummy = pd.get_dummies(employees_test)
         employees_test_dummy.head()
```

```
Out[29]:        satisfaction_level  last_evaluation  number_projects  \
         id
         13001                0.62             0.94                4
         13002                0.38             0.52                2
         13003                0.80             0.77                4
         13004                0.61             0.42                3
         13005                0.61             0.56                4

                average_monthly_hours  time_spent_company  num_work_accidents  \
         id
         13001                    252                   4                   0
         13002                    171                   3                   0
         13003                    194                   3                   0
         13004                    104                   2                   0
         13005                    176                   3                   0

                promotion_last_5years  department_IT  department_RandD  \
         id
         13001                  False              0                 0
         13002                  False              0                 0
         13003                  False              0                 0
         13004                  False              0                 0
```

```
13005                    False            0                 0

       department_accounting  department_hr  department_management  \
id
13001                      1              0                      0
13002                      1              0                      0
13003                      1              0                      0
13004                      0              1                      0
13005                      0              1                      0

       department_marketing  department_product_mng  department_sales  \
id
13001                     0                       0                 0
13002                     0                       0                 0
13003                     0                       0                 0
13004                     0                       0                 0
13005                     0                       0                 0

       department_support  department_technical  salary_high  salary_low  \
id
13001                   0                     0            0           1
13002                   0                     0            0           0
13003                   0                     0            0           0
13004                   0                     0            0           0
13005                   0                     0            0           0

       salary_medium
id
13001              0
13002              1
13003              1
13004              1
13005              1
```

Predict attrition and save in file.

In [30]:
```python
output = pd.DataFrame({
    "id": employees_test_dummy.index,
    "left": model.predict(employees_test_dummy).astype(int)})
output.to_csv(
    path_or_buf="hr_attrition_prediction.csv",
    header=True, index=False)
```

1.6.7 Training on subgroups

There are very few false positives. As mentioned, however, about 5% of employees who left the company are not being identified as such. To get a better idea with which employees the model struggles, we'll look at the subgroups of leavers identified above.

Balance classes through downsampling.

```
In [31]: x = employees_dummy.groupby("leaver_group").apply(
             lambda x: x.sample(n = employees_dummy.groupby("leaver_group").size().min()))
         y = x["leaver_group"]
         x = x.drop(["left", "leaver_group"], axis=1)
         y.value_counts()
```

```
Out[31]: Group 2          735
         Group 3          735
         Group 1          735
         Didn't leave     735
         Name: leaver_group, dtype: int64
```

Set up training and test set.

```
In [32]: x_train, x_test, y_train, y_test = sklearn.model_selection.train_test_split(
             x, y, test_size=0.30)
```

Perform cross validation.

```
In [33]: cv = sklearn.model_selection.GridSearchCV(
             estimator=sklearn.ensemble.RandomForestClassifier(),
             param_grid={"max_depth": [3, 5, 10, 25, 50, 75, 100, None],
                         "n_estimators": [5, 10, 25, 50, 75, 100, 150, 200]},
             n_jobs=6, cv=5, return_train_score=False).fit(x_train, y_train)
```

```
In [34]: print("Best CV score: {:.4f}".format(cv.best_score_))
         print("Best parameters:")
         print("    max_depth={}".format(cv.best_params_["max_depth"]))
         print("    n_estimators={}".format(cv.best_params_["n_estimators"]))
```

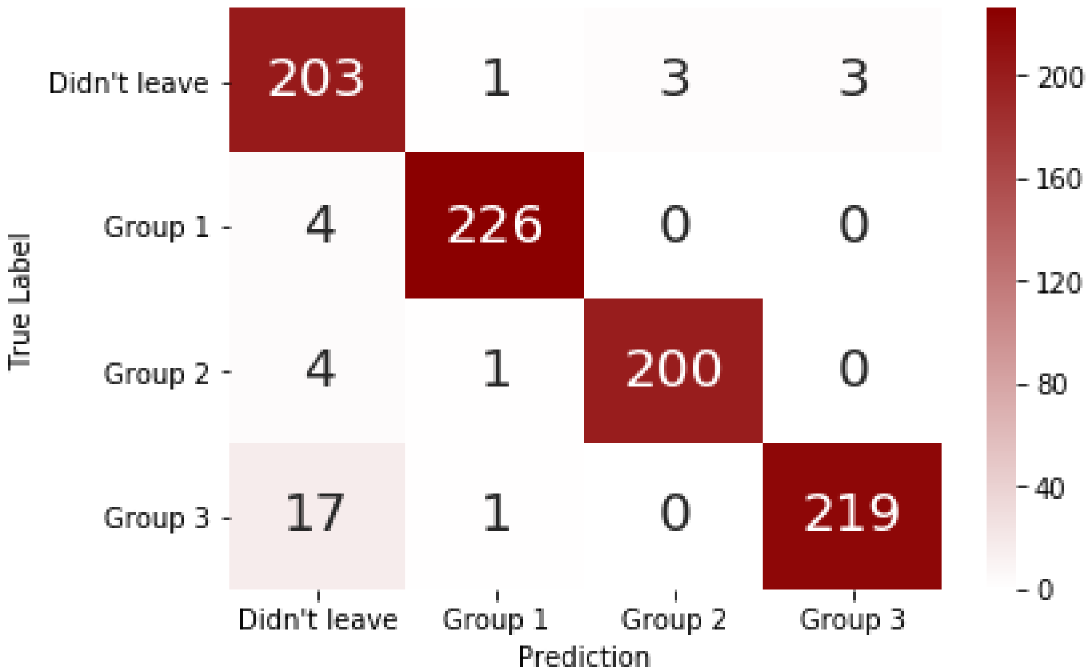
```
Best CV score: 0.9417
Best parameters:
    max_depth=75
    n_estimators=50
```

Fit the model and look at confusion matrix.

```
In [35]: model = cv.best_estimator_.fit(x_train, y_train)
```

```
In [36]: cm = pd.DataFrame({
             "True Label": y_test.values,
             "Prediction": model.predict(x_test)}).groupby(
             ["True Label", "Prediction"]).size().unstack().fillna(0).astype(int)
         sns.heatmap(cm, annot=True, fmt="d", annot_kws={"fontsize": 20}, cmap=colormap)
```

```
Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe02bedbf60>
```



The model struggles primarily with the third group, the employees who leave despite being happy with their work and not overworked. Most likely there are factors not present in this dataset that better describe their reason for leaving.

1.7 Summary

- The strongest predictors of an employee leaving are satisfaction, number of projects, working hours, and tenure at the company
- Employees who leave can be categorized into three broad groups:
  1. Overworked employees who are, on average, unhappy with their work.
  2. Underutilized employees who are, on average, indifferent to their work.
  3. Employees who leave, despite performing well and being happy, possibly due to a lack of career advancement opportunities.
- Salary has a minor effect on the probability of leaving, although this may not be a causal relationship but an accidental correlation, e.g. due to employees with a longer tenure having a higher salary.
- The department in which an employee works appears to play no significant role in predicting attrition.
- A random forest classification model can predict employee attrition with an accuracy of approximately 95%. It struggles more with false negatives than false positives.
  - Training the classifier to identify employee subgroups shows that it struggles most with the third group of leavers, i.e. those who leave despite being happy and performing well. Capturing additional features in the data set, such as career progression beyond the last promotion or personality traits and career wishes, may alleviate this.