```
#import all needed packages up front
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_validate
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
import matplotlib.pyplot as plt
import seaborn as sns
```

It is very important for companies to understand why and when they will lose employees. This view of attrition can aid them in retaining top talent while also better planning for loss.

Here we have a sample dataset where key features of employyes within a company have been kept and a value for whether that employee left (Yes or No) was provided at a snapshot in time.

Our goal here will be to clean the data, select and tune a feaure set, then create and compare a few models which could assist the company in question address the attrition problem.

Credit goes to Prashant Patel (https://www.kaggle.com/patelprashant) from where the dataset has been collected

```
#read in the dataset
df=pd.read_csv("https://www.dropbox.com/scl/fi/zkaa4dkvip5tkuhdtrrru/employee_attrition.csv?rlkey=urstk5jdsezbzj1da69bvjgf1&st=czxxh2kz&dl=1
```

```
df.head()
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	E
0	50.0	No	Travel_Rarely	1126.0	Research & Development	1.0	2	Medical	1	997	
1	36.0	No	Travel_Rarely	216.0	Research & Development	6.0	2	Medical	1	178	
2	21.0	Yes	Travel_Rarely	337.0	Sales	7.0	1	Marketing	1	1780	
3	50.0	No	Travel_Frequently	1246.0	Human Resources	NaN	3	Medical	1	644	
4	52.0	No	Travel_Rarely	994.0	Research & Development	7.0	4	Life Sciences	1	1118	

```
#adjust the target variable to be 1 or 0
df["Attrition"]=df["Attrition"].apply(lambda x: 1 if x=="Yes" else 0)
```

One quick view of what our dataframe looks like.

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1029 entries, 0 to 1028
Data columns (total 35 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Age                       893 non-null    float64
 1   Attrition                 1029 non-null   int64
 2   BusinessTravel            1024 non-null   object
 3   DailyRate                 1002 non-null   float64
 4   Department                1029 non-null   object
 5   DistanceFromHome          934 non-null    float64
 6   Education                 1029 non-null   int64
 7   EducationField            1029 non-null   object
 8   EmployeeCount             1029 non-null   int64
 9   EmployeeNumber            1029 non-null   int64
 10  EnvironmentSatisfaction   1029 non-null   int64
 11  Gender                    1029 non-null   object
 12  HourlyRate                1029 non-null   int64
 13  JobInvolvement            1029 non-null   int64
 14  JobLevel                  1029 non-null   int64
 15  JobRole                   1029 non-null   object
```

```
 16  JobSatisfaction           1029 non-null   int64
 17  MaritalStatus             1024 non-null   object
 18  MonthlyIncome             1029 non-null   int64
 19  MonthlyRate               1029 non-null   int64
 20  NumCompaniesWorked        1029 non-null   int64
 21  Over18                    1029 non-null   object
 22  OverTime                  1029 non-null   object
 23  PercentSalaryHike         1029 non-null   int64
 24  PerformanceRating         1029 non-null   int64
 25  RelationshipSatisfaction  1029 non-null   int64
 26  StandardHours             1029 non-null   int64
 27  StockOptionLevel          1029 non-null   int64
 28  TotalWorkingYears         1029 non-null   int64
 29  TrainingTimesLastYear     1029 non-null   int64
 30  WorkLifeBalance           1029 non-null   int64
 31  YearsAtCompany            1029 non-null   int64
 32  YearsInCurrentRole        1029 non-null   int64
 33  YearsSinceLastPromotion   1029 non-null   int64
 34  YearsWithCurrManager      1029 non-null   int64
dtypes: float64(3), int64(24), object(8)
memory usage: 281.5+ KB
```

We want to take a look at the object columns as these will need to be converted so that they are represented numerically.

```
for col in df.select_dtypes(include='object').columns:
  print(df[col].value_counts())
```

```
BusinessTravel
Travel_Rarely        723
Travel_Frequently    199
Non-Travel           102
Name: count, dtype: int64
Department
Research & Development    676
Sales                     311
Human Resources            42
Name: count, dtype: int64
EducationField
Life Sciences       426
Medical             328
Marketing           110
Technical Degree     82
Other                66
Human Resources      17
Name: count, dtype: int64
Gender
Male      617
Female    412
Name: count, dtype: int64
JobRole
Sales Executive              217
Research Scientist           214
Laboratory Technician        179
Manufacturing Director        95
Healthcare Representative     89
Manager                       73
Sales Representative          66
Research Director             62
Human Resources               34
Name: count, dtype: int64
MaritalStatus
Married     474
Single      320
Divorced    230
Name: count, dtype: int64
Over18
Y    1029
Name: count, dtype: int64
OverTime
No     731
Yes    298
Name: count, dtype: int64
```

We are going to drop some columns which are missing a large number values, have no variablilty, and/or which clearly have collinearity. For the remaining object columns, we will use get_dummies for those, while ensuring we drop one from each set.

```
#use get_dummies to convert object columns to numeric features
df=pd.get_dummies(df, columns=['Gender',"OverTime","BusinessTravel","Department","EducationField","JobRole","MaritalStatus"], drop_first=Tru
```

```
#drop columns that will not be useful, and may be harmful, to our model
df.drop(columns=["Over18","DistanceFromHome","EmployeeCount","EmployeeNumber","DailyRate","HourlyRate"],inplace=True)
```

From our iniital view of the data, we saw that Age was missing a large number of values. However, where attrition is concerned, it is reasonable to assume that Age could be a significant feature. Therefore, we will create a very simple linear regression model to fill in the missing Age values. We will select features for that very simple model based on correlations to the Age field.

```
#lool at all correlations versus the Age field
correlation_matrix = df.corr()
age_correlations = correlation_matrix['Age']
print(age_correlations)
```

```
Age                                1.000000
Attrition                         -0.175555
Education                          0.226646
EnvironmentSatisfaction           -0.024051
JobInvolvement                     0.024176
JobLevel                           0.506348
JobSatisfaction                    0.007670
MonthlyIncome                      0.492360
MonthlyRate                        0.018697
NumCompaniesWorked                 0.298354
PercentSalaryHike                  0.011593
PerformanceRating                  0.007457
RelationshipSatisfaction           0.062533
StandardHours                           NaN
StockOptionLevel                   0.023282
TotalWorkingYears                  0.676650
TrainingTimesLastYear             -0.026077
WorkLifeBalance                   -0.042949
YearsAtCompany                     0.291798
YearsInCurrentRole                 0.218028
YearsSinceLastPromotion            0.178679
YearsWithCurrManager               0.186070
Gender_Male                        0.012663
OverTime_Yes                      -0.013611
BusinessTravel_Travel_Frequently  -0.049995
BusinessTravel_Travel_Rarely       0.072931
Department_Research & Development  0.006722
Department_Sales                  -0.026030
EducationField_Life Sciences      -0.014555
EducationField_Marketing           0.037174
EducationField_Medical             0.016565
EducationField_Other              -0.044943
EducationField_Technical Degree   -0.006064
JobRole_Human Resources           -0.025356
JobRole_Laboratory Technician     -0.139663
JobRole_Manager                    0.285131
JobRole_Manufacturing Director     0.037921
JobRole_Research Director          0.187800
JobRole_Research Scientist        -0.158640
JobRole_Sales Executive            0.026403
JobRole_Sales Representative      -0.208113
MaritalStatus_Married              0.113787
MaritalStatus_Single              -0.132596
Name: Age, dtype: float64
```

```
#create subsets of rows with and without Age value
hasAge=df[df['Age'].notna()]
missingAge=df[df['Age'].isna()]

#based on the correlation matrix, define features for our liner regression model
features=['TotalWorkingYears','JobLevel','MonthlyIncome']

#fit the model
reg=LinearRegression()
reg.fit(hasAge[features],hasAge['Age'])

#predict and assign missing Age values
df.loc[df['Age'].isna(),'Age']=reg.predict(missingAge[features])
```

To further eliminate non-useful features, we will programatically drop any which have no variance.

```
zero_variance=df.columns[df.var()== 0]
df.drop(columns=zero_variance,inplace=True)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1029 entries, 0 to 1028
Data columns (total 42 columns):
 #   Column                             Non-Null Count  Dtype  
---  ------                             --------------  -----  
 0   Age                                1029 non-null   float64
 1   Attrition                          1029 non-null   int64  
 2   Education                          1029 non-null   int64  
 3   EnvironmentSatisfaction            1029 non-null   int64  
 4   JobInvolvement                     1029 non-null   int64  
 5   JobLevel                           1029 non-null   int64  
 6   JobSatisfaction                    1029 non-null   int64  
 7   MonthlyIncome                      1029 non-null   int64  
 8   MonthlyRate                        1029 non-null   int64  
 9   NumCompaniesWorked                 1029 non-null   int64  
 10  PercentSalaryHike                  1029 non-null   int64  
 11  PerformanceRating                  1029 non-null   int64  
 12  RelationshipSatisfaction           1029 non-null   int64  
 13  StockOptionLevel                   1029 non-null   int64  
 14  TotalWorkingYears                  1029 non-null   int64  
 15  TrainingTimesLastYear              1029 non-null   int64  
 16  WorkLifeBalance                    1029 non-null   int64  
 17  YearsAtCompany                     1029 non-null   int64  
 18  YearsInCurrentRole                 1029 non-null   int64  
 19  YearsSinceLastPromotion            1029 non-null   int64  
 20  YearsWithCurrManager               1029 non-null   int64  
 21  Gender_Male                        1029 non-null   int64  
 22  OverTime_Yes                       1029 non-null   int64  
 23  BusinessTravel_Travel_Frequently   1029 non-null   int64  
 24  BusinessTravel_Travel_Rarely       1029 non-null   int64  
 25  Department_Research & Development  1029 non-null   int64  
 26  Department_Sales                   1029 non-null   int64  
 27  EducationField_Life Sciences       1029 non-null   int64  
 28  EducationField_Marketing           1029 non-null   int64  
 29  EducationField_Medical             1029 non-null   int64  
 30  EducationField_Other               1029 non-null   int64  
 31  EducationField_Technical Degree    1029 non-null   int64  
 32  JobRole_Human Resources            1029 non-null   int64  
 33  JobRole_Laboratory Technician      1029 non-null   int64  
 34  JobRole_Manager                    1029 non-null   int64  
 35  JobRole_Manufacturing Director     1029 non-null   int64  
 36  JobRole_Research Director          1029 non-null   int64  
 37  JobRole_Research Scientist         1029 non-null   int64  
 38  JobRole_Sales Executive            1029 non-null   int64  
 39  JobRole_Sales Representative       1029 non-null   int64  
 40  MaritalStatus_Married              1029 non-null   int64  
 41  MaritalStatus_Single               1029 non-null   int64  
dtypes: float64(1), int64(41)
memory usage: 337.8 KB
```

We now have a complete dataset, which is purely numeric, and where we have a moderate set of features where obvious collinearity and lack of variance have been eliminated.

We will next train a logistic regression model and use the coefficients to see if we can further eliminate features.

```
x=df.loc[:, df.columns != 'Attrition'] #feature set
y=df["Attrition"] #target variable

#split the data s.t. we have 20% for testing and 80% for training
X_train, X_test, y_train, y_test = train_test_split(x, y, random_state=2)

#train a lr using liblinear since it is generally good for small training sets
lr = LogisticRegression(solver='liblinear', random_state=2)
lr.fit(X_train, y_train)

print('# of iterations %s' % lr.n_iter_[0])

test_score = lr.score(X_test, y_test)
train_score = lr.score(X_train, y_train)

print('Score on training data: ', train_score)
print('Score on test data: ', test_score)
```

```
# of iterations 29
Score on training data:  0.8780804150453956
Score on test data:  0.8643410852713178
```

Now that the model is trained, we can inspect the coefficients.

```
coefficients = lr.coef_
feature_names = X_train.columns
coefficients_df = pd.DataFrame(coefficients, columns=feature_names)
pd.set_option('display.max_columns', None)
coefficients_df.head()
```

	Age	Education	EnvironmentSatisfaction	JobInvolvement	JobLevel	JobSatisfaction	MonthlyIncome	MonthlyRate	NumCompaniesWorkec
0	0.00662	-0.004683	-0.311567	-0.290681	-0.057589	-0.220821	-0.000034	0.00002	0.21055

MontlyRate and MonthlyIncome are variables very likely to have collinearty that were missed earlier. We will remove them now.

Education seems to have very low impact on the model. We will therefore remove it in an attempt to simplify the model.

Although Age turns out to seemingly have low impact as well, we will leave it for now as we might could create a new feature by crossing this with some other variable.

```
df.drop(columns=["MonthlyRate","MonthlyIncome","Education"],inplace=True)
```

Now we will trian a new model in the same method with the new feature set.

```
x=df.loc[:, df.columns != 'Attrition']
y=df["Attrition"]

X_train, X_test, y_train, y_test = train_test_split(x, y, random_state=2)

lr = LogisticRegression(solver='liblinear', random_state=2)
lr.fit(X_train, y_train)

print('# of iterations %s' % lr.n_iter_[0])

test_score = lr.score(X_test, y_test)
train_score = lr.score(X_train, y_train)

print('Score on training data: ', train_score)
print('Score on test data: ', test_score)
```

```
# of iterations 15
Score on training data:  0.8832684824902723
Score on test data:  0.8914728682170543
```

We have a slight improvement - notably on the test data meaning we have possible reduced overfitting by a bit.

```
#create a dataframe to track our scores on the following models
scores_df=pd.DataFrame(columns=["Model","Method","Accuracy"])
```

In the following sections we will take this aproach:

- Use 5-fold cross validation to get the average accuracy for a model
- Use grid search 5 fold cross validation to tune a set of parameters for the model within a restircted value set
- Register the average and best average accuracy for the above in a dataframe

This will be applied across Logistic Regression, Random Forest, and Gradient Boosting models.

```
#use CV on a logistic regression model
cv_results = cross_validate(
    lr, x, y, cv=5,
    scoring=['accuracy', 'precision', 'recall', 'f1'],  # Metrics to calculate
    return_train_score=True  # If you want to see the train scores as well
)

print("Average accuracy:", cv_results['test_accuracy'].mean())
print("Average precision:", cv_results['test_precision'].mean())
print("Average recall:", cv_results['test_recall'].mean())
print("Average F1 score:", cv_results['test_f1'].mean())
```

```
#save the accuracy
new_row=pd.DataFrame({'Model': ['Logistic Regression'], 'Method': ['Default'], "Accuracy": [ cv_results['test_accuracy'].mean()]})
scores_df = pd.concat([scores_df, new_row], ignore_index=True)
```

```
Average accuracy: 0.8717120530428606
Average precision: 0.7335943724044411
Average recall: 0.41460317460317453
Average F1 score: 0.5247012618734046
<ipython-input-355-61170fef1c03>:15: FutureWarning: The behavior of DataFrame concatenation with empty or all-NA entries is deprecated.
  scores_df = pd.concat([scores_df, new_row], ignore_index=True)
```

```
#use grid search on the logistic regression model
param_grid = {
    'C': [0.01, 0.1, 1, 10],
    'penalty': ['l1','l2'],
    'solver': ['liblinear']
}
grid_search = GridSearchCV(lr, param_grid, cv=5, scoring='accuracy')
grid_search.fit(x, y)
print("Best parameters:", grid_search.best_params_)
print("Best cross-validation accuracy:", grid_search.best_score_)

new_row=pd.DataFrame({'Model': ['Logistic Regression'], 'Method': ['Param Search'], "Accuracy": [grid_search.best_score_]})
scores_df = pd.concat([scores_df, new_row], ignore_index=True)
```

```
Best parameters: {'C': 0.1, 'penalty': 'l2', 'solver': 'liblinear'}
Best cross-validation accuracy: 0.8736585365853659
```

```
#use CV on a random forest model
rf=RandomForestClassifier(random_state=42)
cv_results = cross_validate(
    rf, x, y, cv=5,
    scoring=['accuracy', 'precision', 'recall', 'f1'],  # Metrics to calculate
    return_train_score=True  # If you want to see the train scores as well
)

print("Average accuracy:", cv_results['test_accuracy'].mean())
print("Average precision:", cv_results['test_precision'].mean())
print("Average recall:", cv_results['test_recall'].mean())
print("Average F1 score:", cv_results['test_f1'].mean())

new_row=pd.DataFrame({'Model': ['Random Forest'], 'Method': ['Default'], "Accuracy": [cv_results['test_accuracy'].mean()]})
scores_df = pd.concat([scores_df, new_row], ignore_index=True)
```

```
Average accuracy: 0.8503480937721998
Average precision: 0.7758823529411765
Average recall: 0.19857142857142857
Average F1 score: 0.30926819755253276
```

```
#use grid search on a random forest model
param_grid = {
    'n_estimators': [10, 20, 30],
    'max_depth': [5, 10],
    'max_features': ['sqrt', 'log2'],
    'criterion': ['gini', 'entropy']
}

grid_search = GridSearchCV(rf, param_grid, cv=5, scoring='accuracy')
grid_search.fit(x, y)
print("Best parameters:", grid_search.best_params_)
print("Best cross-validation accuracy:", grid_search.best_score_)

new_row=pd.DataFrame({'Model': ['Random Forest'], 'Method': ['Param Search'], "Accuracy": [grid_search.best_score_]})
scores_df = pd.concat([scores_df, new_row], ignore_index=True)
```

```
Best parameters: {'criterion': 'entropy', 'max_depth': 10, 'max_features': 'log2', 'n_estimators': 30}
Best cross-validation accuracy: 0.8513189675586077
```

```
#use CV on a gradient boosting model
gb = GradientBoostingClassifier(random_state=42)
cv_results = cross_validate(
    gb, x, y, cv=5,
    scoring=['accuracy', 'precision', 'recall', 'f1'],
    return_train_score=True
```

```
)

print("Average accuracy:", cv_results['test_accuracy'].mean())
print("Average precision:", cv_results['test_precision'].mean())
print("Average recall:", cv_results['test_recall'].mean())
print("Average F1 score:", cv_results['test_f1'].mean())

new_row=pd.DataFrame({'Model': ['Gradient Boosting'], 'Method': ['Default'], "Accuracy": [cv_results['test_accuracy'].mean()]})
scores_df = pd.concat([scores_df, new_row], ignore_index=True)
```

```
Average accuracy: 0.8658726024153445
Average precision: 0.7259006353124
Average recall: 0.3685714285714286
Average F1 score: 0.4807791811247844
```

```
#use grid search on a gradient boosting model
param_grid = {
    'n_estimators': [10, 20, 30],
    'max_depth': [5, 10],
    'learning_rate': [0.01, 0.1, 0.2],
    'subsample': [0.8, 1.0],
    'max_features': ['sqrt', 'log2']
}

grid_search = GridSearchCV(gb, param_grid, cv=5, scoring='accuracy')
grid_search.fit(x, y)
print("Best parameters:", grid_search.best_params_)
print("Best cross-validation accuracy:", grid_search.best_score_)

new_row=pd.DataFrame({'Model': ['Gradient Boosting'], 'Method': ['Param Search'], "Accuracy": [grid_search.best_score_]})
scores_df = pd.concat([scores_df, new_row], ignore_index=True)
```

```
Best parameters: {'learning_rate': 0.2, 'max_depth': 5, 'max_features': 'log2', 'n_estimators': 30, 'subsample': 1.0}
Best cross-validation accuracy: 0.8590954297892492
```

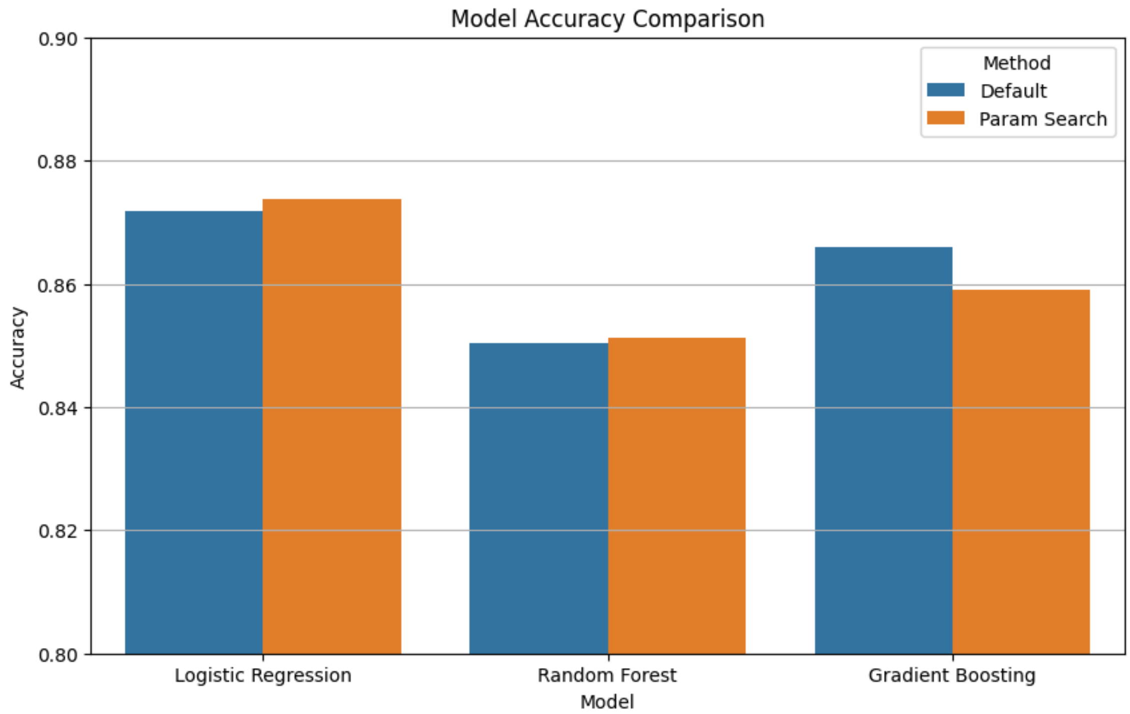
Let's take a look at the results, graphically.

```
plt.figure(figsize=(10, 6))
sns.barplot(data=scores_df, x='Model', y='Accuracy', hue='Method')

plt.title('Model Accuracy Comparison')
plt.xlabel('Model')
plt.ylabel('Accuracy')
plt.ylim(0.8, 0.9)
plt.legend(title='Method')
plt.grid(axis='y')

plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949: FutureWarning: When grouping with a length-1 list-like, you will need to p
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949: FutureWarning: When grouping with a length-1 list-like, you will need to p
  data_subset = grouped_data.get_group(pd_key)
```



The overall best model was a parameter-tuned Liblinear Logistic Regression classifier.