



Employee Performance Analysis

DAT7 Capstone Project

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```
In [6]: df = pd.read_csv ('Data/Employee_Performance_Data.csv')
df
```

```
Out[6]:
```

	EmpNumber	Age	Gender	EducationBackground	MaritalStatus	EmpDepartment	EmpJobRole	BusinessTravelFrequency	DistanceFromHome
0	E1001000	32	Male	Marketing	Single	Sales	Sales Executive	Travel_Rarely	1
1	E1001006	47	Male	Marketing	Single	Sales	Sales Executive	Travel_Rarely	1
2	E1001007	40	Male	Life Sciences	Married	Sales	Sales Executive	Travel_Frequently	1
3	E1001009	41	Male	Human Resources	Divorced	Human Resources	Manager	Travel_Rarely	1
4	E1001010	60	Male	Marketing	Single	Sales	Sales Executive	Travel_Rarely	1
...
1195	E100992	27	Female	Medical	Divorced	Sales	Sales Executive	Travel_Frequently	1
1196	E100993	37	Male	Life Sciences	Single	Development	Senior Developer	Travel_Rarely	1
1197	E100994	50	Male	Medical	Married	Development	Senior Developer	Travel_Rarely	1
1198	E100995	24	Female	Medical	Single	Data Science	Data	Travel_Rarely	1

Background Knowledge About The Dataset

Business & Goal of this project

- Analyze the Employee dataset
- Identify key factors affecting performance ratings
- Accurately predict performance outcomes
- Inform HR decision-making
- Boost employee performance
- Support organizational growth.



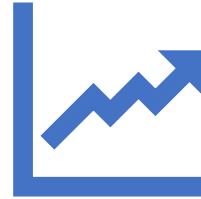
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"What do you mean you don't know what I've been up to recently?! Just follow me on Twitter!"

Key Findings



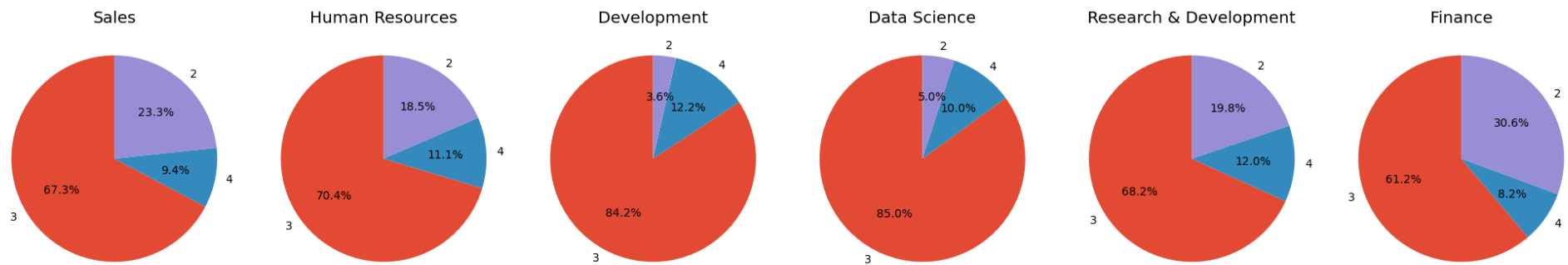
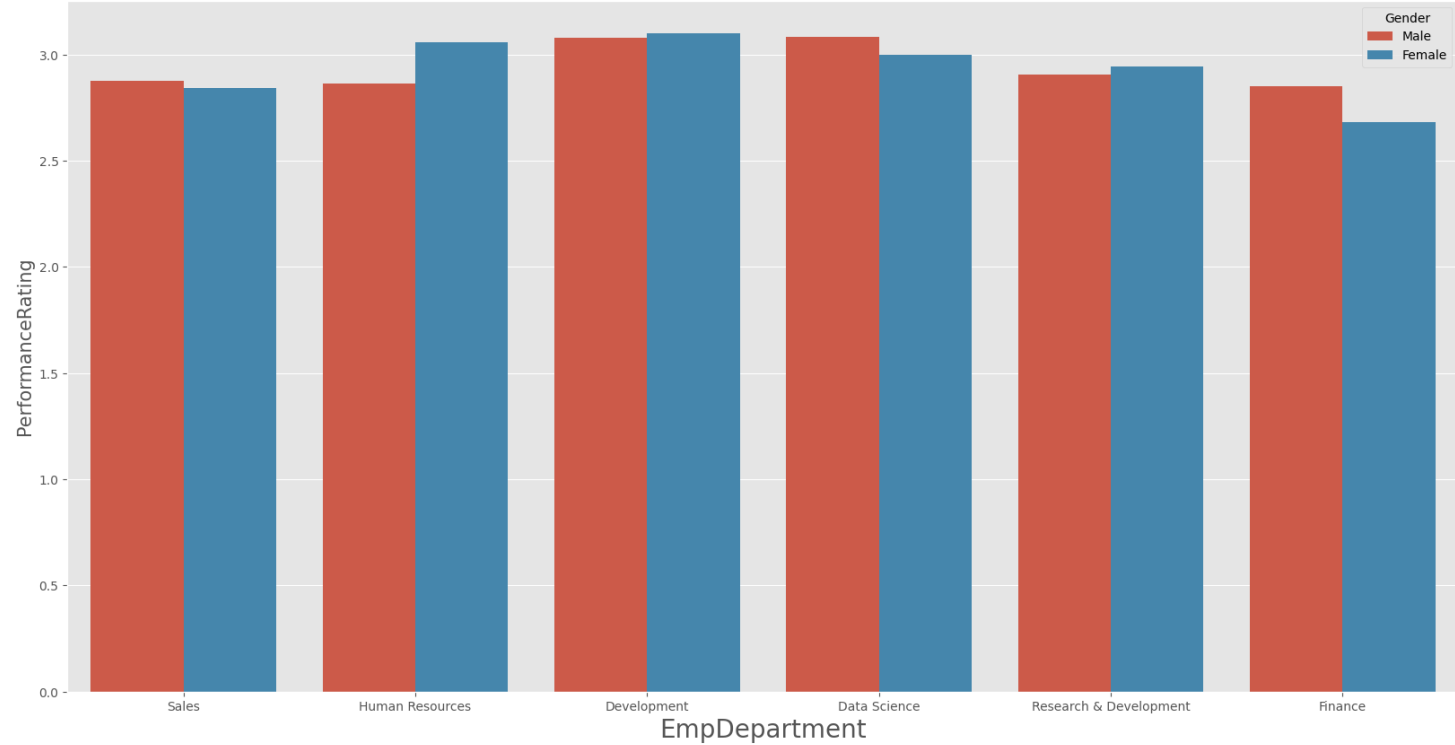
Department-wise Performance
Rating



Top 3 Determinants Impacting
Employee Performance



Key Takeaways for HR and
Organizations

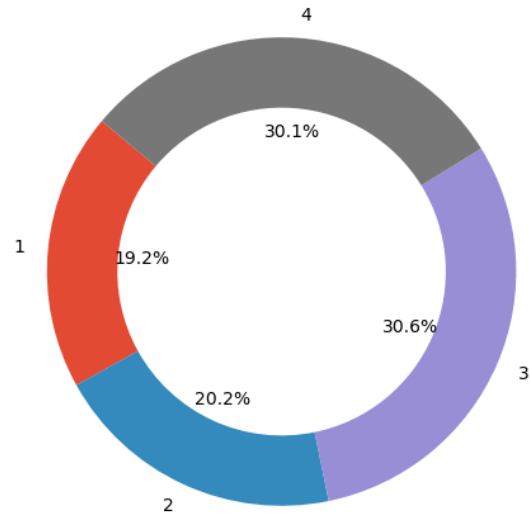


Department-wise Performance Rating

1. Low
2. Good
3. **Excellent** - All the departments have almost 60-80% excellent employee performance rate
4. Outstanding



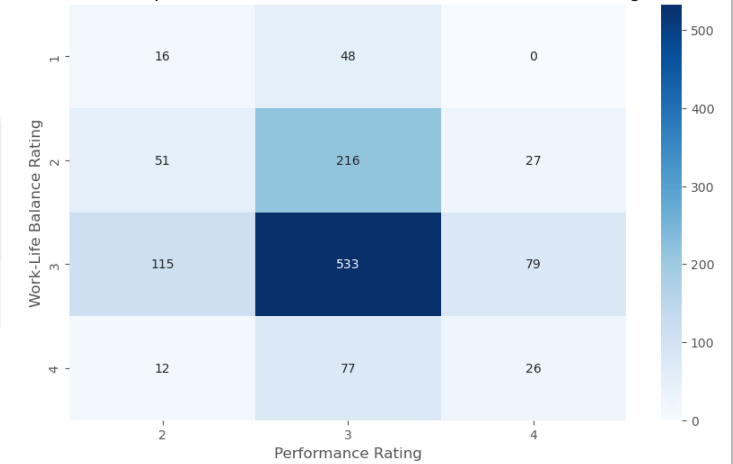
Distribution of Employee Environment Satisfaction



```
In [22]: # 2.Employee last salary hike percent  
pd.crosstab(df['EmplLastSalaryHikePercent'],df['PerformanceRating'],margins=True)
```

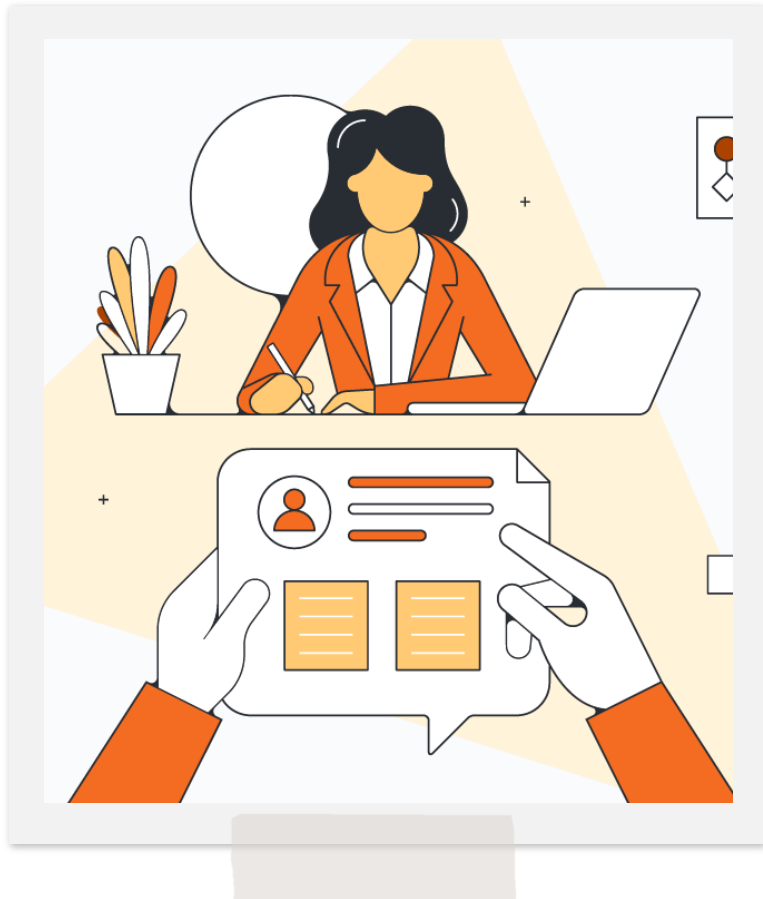
		PerformanceRating			
		2	3	4	All
EmplLastSalaryHikePercent	11	28	140	1	169
	12	30	123	2	155
	13	27	138	3	168
	14	28	140	4	172
	15	11	67	4	82
	16	12	54	2	68
	17	9	55	3	67
	18	10	63	0	73
	19	10	51	2	63
	20	9	14	27	50
	21	4	6	24	34
	22	7	13	27	47
	23	4	2	15	21
	24	2	5	11	18
	25	3	3	7	13
	All	194	874	132	1200

Relationship between Work-Life Balance and Performance Rating



Top 3 Determinants Impacting Employee Performance

Key Takeaways for HR and Organizations



- **Focus on Employee Environment Satisfaction**
- **Review Compensation Regularly**
- **Promote Work-Life Balance**
- **Continuous Learning & Development**
- **Feedback Mechanism**
- **Data-Driven Decision Making**
- **Promote Collaboration**
- **Recognition and Reward System**
- **Career Path Clarity**

Regression Analysis Insights

Test RMSE: 0.3836557985067259

Out[104]: OLS Regression Results

Dep. Variable:	PerformanceRating	R-squared:	0.532			
Model:	OLS	Adj. R-squared:	0.493			
Method:	Least Squares	F-statistic:	13.68			
Date:	Fri, 06 Oct 2023	Prob (F-statistic):	3.40e-96			
Time:	21:48:07	Log-Likelihood:	-351.30			
No. Observations:	900	AIC:	842.6			
Df Residuals:	830	BIC:	1179.			
Df Model:	69					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
Intercept	2.0227	0.160	12.629	0.000	1.708	2.337
Age	-0.0014	0.002	-0.793	0.428	-0.005	0.002
DistanceFromHome	-0.0031	0.002	-1.940	0.053	-0.006	3.59e-05
EmpEducationLevel	0.0191	0.013	1.522	0.129	-0.006	0.044
EmpHourlyRate	-0.0015	0.001	-2.472	0.014	-0.003	-0.000
EmpJobInvolvement	0.0059	0.019	0.316	0.752	-0.031	0.042
EmpJobLevel	-0.0002	0.019	-0.008	0.993	-0.037	0.037
EmpJobSatisfaction	-0.0029	0.012	-0.247	0.805	-0.026	0.020
NumCompaniesWorked	-0.0003	0.006	-0.056	0.956	-0.012	0.011
TotalWorkExperienceInYears	0.0010	0.003	0.308	0.758	-0.005	0.007
TrainingTimesLastYear	-0.0089	0.018	-0.482	0.630	-0.045	0.027
ExperienceYearsAtThisCompany	0.0026	0.005	0.546	0.585	-0.007	0.012

best_score: 0.8627700127064803 using 1 solver: newton-cg, penalty: l2, C: 0.1

```
In [125]: LR2 = LogisticRegression(C=0.1,penalty='l2',solver='newton-cg')
LR2.fit(x_sm,y_sm)
y_predict_lr2 = LR2.predict(x_test)
accuracy_score(y_test,y_predict_lr2)
```

Out[125]: 0.8627700127064803

```
In [126]: #When we use logistic regression, we're trying to put things into categories. A confusion matrix and classification report h
from sklearn.metrics import classification_report,confusion_matrix
print("Confusion Matrix----",confusion_matrix(y_test,y_predict_lr2))
print("Classification Report----",classification_report(y_test,y_predict_lr2))
```

```
Confusion Matrix---- [[247  16  15]
 [ 31 190  29]
 [  4  13 242]]
Classification Report----
```

		precision	recall	f1-score	support
	2	0.88	0.89	0.88	278
	3	0.87	0.76	0.81	250
	4	0.85	0.93	0.89	259
accuracy			0.86		787
macro avg	0.86	0.86	0.86		787
weighted avg	0.86	0.86	0.86		787



Thank You

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