Bank Customer Data Prep

Clean and explore bank customer data to prepare it for machine learning models

In [1]:
```
# Objective 1
# Import & QA the data
# Your first objective is to import & join two customer data tables, then remove duplicate rows & columns and fill in missing values.
```

In [2]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

In [3]:
```
# Import the data from both tabs in the "Bank_Churn_Messy" Excel file
customer = pd.read_excel('Bank_Churn_Messy.xlsx', sheet_name=0)
```

In [4]:
```
customer
```

Out[4]:

	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	EstimatedSalary
0	15634602	Hargrave	619	FRA	Female	42.0	2	€101348.88
1	15647311	Hill	608	Spain	Female	41.0	1	€112542.58
2	15619304	Onio	502	French	Female	42.0	8	€113931.57
3	15701354	Boni	699	FRA	Female	39.0	1	€93826.63
4	15737888	Mitchell	850	Spain	Female	43.0	2	€79084.1
...	...	...	...	...	...	...	...	...
9996	15569892	Johnstone	516	French	Male	35.0	10	€101699.77
9997	15584532	Liu	709	FRA	Female	36.0	7	€42085.58
9998	15682355	Sabbatini	772	Germany	Male	42.0	3	€92888.52
9999	15628319	Walker	792	French	Female	28.0	4	€38190.78
10000	15628319	Walker	792	French	Female	28.0	4	€38190.78

10001 rows × 8 columns

In [5]:
```
account = pd.read_excel('Bank_Churn_Messy.xlsx', sheet_name=1)
```

In [6]:
```
account
```

Out[6]:

	CustomerId	Balance	NumOfProducts	HasCrCard	Tenure	IsActiveMember	Exited
0	15634602	€0.0	1	Yes	2	Yes	1
1	15634602	€0.0	1	Yes	2	Yes	1
2	15647311	€83807.86	1	Yes	1	Yes	0
3	15619304	€159660.8	3	No	8	No	1
4	15701354	€0.0	2	No	1	No	0
...	...	...	...	...	...	...	...
9997	15569892	€57369.61	1	Yes	10	Yes	0
9998	15584532	€0.0	1	Yes	7	Yes	1
9999	15682355	€75075.31	2	No	3	No	1
10000	15628319	€130142.79	1	No	4	No	0
10001	15628319	€130142.79	1	No	4	No	0

10002 rows × 7 columns

In [7]:
```
# Use a left join to join "Account_Info" to "Customer_Info" using the CustomerID column
```

In [8]:
```
df = account.merge(customer, how='left', on='CustomerId')
```

In [9]:
```
df
```

Out[9]:

	CustomerId	Balance	NumOfProducts	HasCrCard	Tenure_x	IsActiveMember	Exited	Surname	CreditScore	Geography	Gender	Age	Tenure_y	EstimatedSalary
0	15634602	€0.0	1	Yes	2	Yes	1	Hargrave	619	FRA	Female	42.0	2	€101348.88
1	15634602	€0.0	1	Yes	2	Yes	1	Hargrave	619	FRA	Female	42.0	2	€101348.88
2	15647311	€83807.86	1	Yes	1	Yes	0	Hill	608	Spain	Female	41.0	1	€112542.58
3	15619304	€159660.8	3	No	8	No	1	Onio	502	French	Female	42.0	8	€113931.57
4	15701354	€0.0	2	No	1	No	0	Boni	699	FRA	Female	39.0	1	€93826.63
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9999	15682355	€75075.31	2	No	3	No	1	Sabbatini	772	Germany	Male	42.0	3	€92888.52
10000	15628319	€130142.79	1	No	4	No	0	Walker	792	French	Female	28.0	4	€38190.78
10001	15628319	€130142.79	1	No	4	No	0	Walker	792	French	Female	28.0	4	€38190.78
10002	15628319	€130142.79	1	No	4	No	0	Walker	792	French	Female	28.0	4	€38190.78
10003	15628319	€130142.79	1	No	4	No	0	Walker	792	French	Female	28.0	4	€38190.78

10004 rows × 14 columns

In [10]:
```
# Check for and remove duplicate rows and columns
df.drop_duplicates(inplace=True, ignore_index=True)
```

In [11]:
```
df
```

Out[11]:

	CustomerId	Balance	NumOfProducts	HasCrCard	Tenure_x	IsActiveMember	Exited	Surname	CreditScore	Geography	Gender	Age	Tenure_y	EstimatedSalary
0	15634602	€0.0	1	Yes	2	Yes	1	Hargrave	619	FRA	Female	42.0	2	€101348.88
1	15647311	€83807.86	1	Yes	1	Yes	0	Hill	608	Spain	Female	41.0	1	€112542.58
2	15619304	€159660.8	3	No	8	No	1	Onio	502	French	Female	42.0	8	€113931.57
3	15701354	€0.0	2	No	1	No	0	Boni	699	FRA	Female	39.0	1	€93826.63
4	15737888	€125510.82	1	Yes	2	Yes	0	Mitchell	850	Spain	Female	43.0	2	€79084.1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	15606229	€0.0	2	No	5	No	0	Obijiaku	771	France	Male	39.0	5	€96270.64
9996	15569892	€57369.61	1	Yes	10	Yes	0	Johnstone	516	French	Male	35.0	10	€101699.77
9997	15584532	€0.0	1	Yes	7	Yes	1	Liu	709	FRA	Female	36.0	7	€42085.58
9998	15682355	€75075.31	2	No	3	No	1	Sabbatini	772	Germany	Male	42.0	3	€92888.52
9999	15628319	€130142.79	1	No	4	No	0	Walker	792	French	Female	28.0	4	€38190.78

10000 rows × 14 columns

In [12]:
```
df.drop('Tenure_y', axis=1, inplace=True)
```

In [13]:
```
df.rename(columns={'Tenure_x': 'Tenure'}, inplace=True)
```

In [14]:
```
df
```

Out[14]:

	CustomerId	Balance	NumOfProducts	HasCrCard	Tenure	IsActiveMember	Exited	Surname	CreditScore	Geography	Gender	Age	EstimatedSalary
0	15634602	€0.0	1	Yes	2	Yes	1	Hargrave	619	FRA	Female	42.0	€101348.88
1	15647311	€83807.86	1	Yes	1	Yes	0	Hill	608	Spain	Female	41.0	€112542.58
2	15619304	€159660.8	3	No	8	No	1	Onio	502	French	Female	42.0	€113931.57
3	15701354	€0.0	2	No	1	No	0	Boni	699	FRA	Female	39.0	€93826.63
4	15737888	€125510.82	1	Yes	2	Yes	0	Mitchell	850	Spain	Female	43.0	€79084.1
...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	15606229	€0.0	2	No	5	No	0	Obijiaku	771	France	Male	39.0	€96270.64
9996	15569892	€57369.61	1	Yes	10	Yes	0	Johnstone	516	French	Male	35.0	€101699.77
9997	15584532	€0.0	1	Yes	7	Yes	1	Liu	709	FRA	Female	36.0	€42085.58
9998	15682355	€75075.31	2	No	3	No	1	Sabbatini	772	Germany	Male	42.0	€92888.52
9999	15628319	€130142.79	1	No	4	No	0	Walker	792	French	Female	28.0	€38190.78

10000 rows × 13 columns

In [15]:
```
# Objective 2
# Clean the data
# Your second objective is to clean the data by fixing inconsistencies in labeling, handling erroneous values, and fixing currency fields.
```

In [16]:
```
# Check the data types for each column and make any necessary fixes
```

In [17]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 13 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   CustomerId       10000 non-null  int64  
 1   Balance          10000 non-null  object 
 2   NumOfProducts    10000 non-null  int64  
 3   HasCrCard        10000 non-null  object 
 4   Tenure           10000 non-null  int64  
 5   IsActiveMember   10000 non-null  object 
 6   Exited           10000 non-null  int64  
 7   Surname          9997 non-null   object 
 8   CreditScore      10000 non-null  int64  
 9   Geography        10000 non-null  object 
 10  Gender           10000 non-null  object 
 11  Age              9997 non-null   float64
 12  EstimatedSalary  10000 non-null  object 
dtypes: float64(1), int64(5), object(7)
memory usage: 1015.8+ KB
```

In [18]:
```
df.dropna(inplace=True, ignore_index=True)
```

In [19]:
```
df['Age'] = df['Age'].astype('int')
```

In [20]:
```
columns = ['Balance', 'EstimatedSalary']

for col in columns:
    df[col] = df[col].str.replace('€', '', regex=False)
    df[col] = pd.to_numeric(df[col])
```

In [21]:
```
df
```

Out[21]:

	CustomerId	Balance	NumOfProducts	HasCrCard	Tenure	IsActiveMember	Exited	Surname	CreditScore	Geography	Gender	Age	EstimatedSalary
0	15634602	0.00	1	Yes	2	Yes	1	Hargrave	619	FRA	Female	42	101348.88
1	15647311	83807.86	1	Yes	1	Yes	0	Hill	608	Spain	Female	41	112542.58
2	15619304	159660.80	3	No	8	No	1	Onio	502	French	Female	42	113931.57
3	15701354	0.00	2	No	1	No	0	Boni	699	FRA	Female	39	93826.63
4	15737888	125510.82	1	Yes	2	Yes	0	Mitchell	850	Spain	Female	43	79084.10
...	...	...	...	...	...	...	...	...	...	...	...	...	...
9992	15606229	0.00	2	No	5	No	0	Obijiaku	771	France	Male	39	96270.64
9993	15569892	57369.61	1	Yes	10	Yes	0	Johnstone	516	French	Male	35	101699.77
9994	15584532	0.00	1	Yes	7	Yes	1	Liu	709	FRA	Female	36	42085.58
9995	15682355	75075.31	2	No	3	No	1	Sabbatini	772	Germany	Male	42	92888.52
9996	15628319	130142.79	1	No	4	No	0	Walker	792	French	Female	28	38190.78

9997 rows × 13 columns

In [22]:
```
#Q: Replace missing values in categorical columns with "MISSING", and missing values in numeric columns with the median
#A: I've deleted these rows, there was only 3 rows...
```

In [23]:
```
# Profile the numeric columns in the data. Are there any extreme or non-sensical values?
# If so, impute them with the median of the column.
df.describe()
```

Out[23]:

	CustomerId	Balance	NumOfProducts	Tenure	Exited	CreditScore	Age	EstimatedSalary
count	9.997000e+03	9997.000000	9997.000000	9997.000000	9997.000000	9997.000000	9997.000000	9997.000000
mean	1.569094e+07	76482.679807	1.530359	5.013204	0.203761	650.545364	38.922077	100092.222656
std	7.193443e+04	62397.174721	0.581669	2.892364	0.402814	96.657932	10.489072	57518.775702
min	1.556570e+07	0.000000	1.000000	0.000000	0.000000	350.000000	18.000000	11.580000
25%	1.562853e+07	0.000000	1.000000	3.000000	0.000000	584.000000	32.000000	50974.570000
50%	1.569073e+07	97188.620000	1.000000	5.000000	0.000000	652.000000	37.000000	100236.020000
75%	1.575323e+07	127642.440000	2.000000	7.000000	0.000000	718.000000	44.000000	149399.700000
max	1.581569e+07	250898.090000	4.000000	10.000000	1.000000	850.000000	92.000000	199992.480000

In [24]:
```
df[df.EstimatedSalary < 90]
```

Out[24]:

	CustomerId	Balance	NumOfProducts	HasCrCard	Tenure	IsActiveMember	Exited	Surname	CreditScore	Geography	Gender	Age	EstimatedSalary
2360	15791053	122917.71	1	Yes	4	Yes	1	Lucciano	709	Germany	Male	45	11.58

In [25]:
```
df.loc[2362:2362, "EstimatedSalary"] = df.EstimatedSalary.median()
```

In [26]:
```
df.loc[2362:2362, "EstimatedSalary"]
```

Out[26]:
```
2362    100236.02
Name: EstimatedSalary, dtype: float64
```

In [27]:
```
# Combine any variations in country names in the "Geography" column to a single value per country
df.Geography.value_counts()
```

Out[27]:
```
Geography
Germany    2508
Spain      2476
France     1740
French     1655
FRA        1618
Name: count, dtype: int64
```

In [28]:
```
columns = ['French', 'FRA']

for col in columns:
    df.Geography = np.where(df.Geography == col, "France", df.Geography)
```

In [29]:
```
# Objective 3
# Explore the data
# Your third objective is to explore the target variable and look at feature-target relationships for categorical and numeric fields.
```

In [30]:
```
# Build a bar chart displaying the count of churners (Exited=1) vs. non-churners (Exited=0)
churners = (df['Exited'] == 1).sum()
non_churners = (df['Exited'] == 0).sum()
```

In [31]:
```
churn_count = {
    'Group': ['Churners', 'Non-Churners'],
    'Count': [churners, non_churners]
    }

churn_df = pd.DataFrame(churn_count)
```

In [32]:
```
churn_df
```

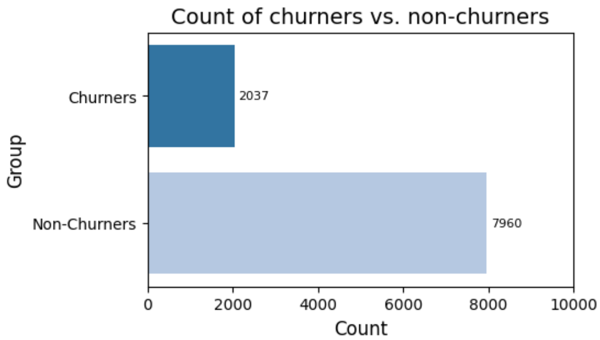
Out[32]:

	Group	Count
0	Churners	2037
1	Non-Churners	7960

In [33]:
```
plt.figure(figsize=(5, 3))
sns.barplot(data=churn_df, x='Count', y='Group', palette='tab20', hue='Group', legend=False);

plt.title('Count of churners vs. non-churners', fontsize=14);
plt.xlabel('Count', fontsize=12);
plt.ylabel('Group', fontsize=12);
plt.xlim(0, 10000);
```

```python
for i, row in enumerate(churn_df.itertuples()):
    plt.text(row.Count + 100, i, f"{row.Count:}",
             va='center', fontsize=8)
```

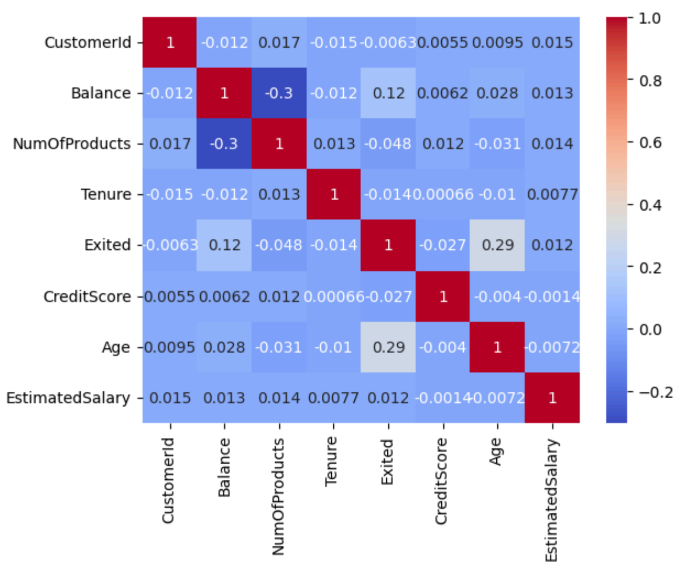


In [34]:
```python
# Explore the variables vs. the target
df.corr(numeric_only=True)
```

Out[34]:

	CustomerId	Balance	NumOfProducts	Tenure	Exited	CreditScore	Age	EstimatedSalary
CustomerId	1.000000	-0.012257	0.016968	-0.014702	-0.006254	0.005495	0.009540	0.015328
Balance	-0.012257	1.000000	-0.304218	-0.012336	0.118582	0.006193	0.028192	0.012758
NumOfProducts	0.016968	-0.304218	1.000000	0.013319	-0.047966	0.012084	-0.030709	0.014187
Tenure	-0.014702	-0.012336	0.013319	1.000000	-0.014073	0.000657	-0.010040	0.007732
Exited	-0.006254	0.118582	-0.047966	-0.014073	1.000000	-0.027184	0.285329	0.012072
CreditScore	0.005495	0.006193	0.012084	0.000657	-0.027184	1.000000	-0.004012	-0.001416
Age	0.009540	0.028192	-0.030709	-0.010040	0.285329	-0.004012	1.000000	-0.007236
EstimatedSalary	0.015328	0.012758	0.014187	0.007732	0.012072	-0.001416	-0.007236	1.000000

In [35]:
```python
sns.heatmap(df.corr(numeric_only=True), cmap='coolwarm', annot=True);
```



In [36]:
```python
# and look at the percentage of Churners by "Geography" and "Gender"
```

In [37]:
```python
churn_geo = df.groupby(['Exited', 'Geography']).size().reset_index(name='Count')
churn_geo['Pct'] = churn_geo.groupby('Exited')['Count'].transform(lambda x: x / x.sum())
```

In [38]:
```python
churn_geo
```

Out[38]:

	Exited	Geography	Count	Pct
0	0	France	4203	0.528015
1	0	Germany	1694	0.212814
2	0	Spain	2063	0.259171
3	1	France	810	0.397644
4	1	Germany	814	0.399607
5	1	Spain	413	0.202749

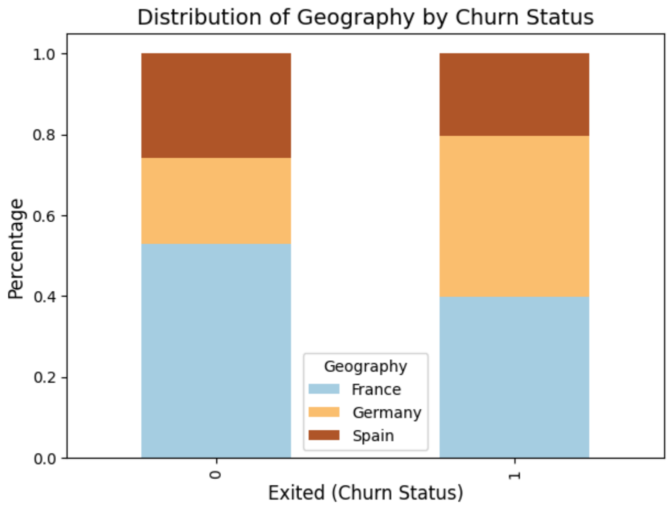
In [39]:
```python
geo_pivot = churn_geo.pivot(index='Exited', columns='Geography', values='Pct')
```

In [40]:
```python
geo_pivot
```

Out[40]:

Geography	France	Germany	Spain
Exited			
0	0.528015	0.212814	0.259171
1	0.397644	0.399607	0.202749

In [41]:
```python
fig, ax = plt.subplots(figsize=(7, 5))
geo_pivot.plot(kind='bar', stacked=True, ax=ax, colormap='Paired')
ax.set_title('Distribution of Geography by Churn Status', fontsize=14)
ax.set_xlabel('Exited (Churn Status)', fontsize=12)
ax.set_ylabel('Percentage', fontsize=12)
ax.legend(title='Geography', fontsize=10)
plt.show()
```



In [42]:
```python
churn_gender = df.groupby(['Exited', 'Gender']).size().reset_index(name='Count')
churn_gender['Pct'] = churn_gender.groupby('Exited')['Count'].transform(lambda x: x / x.sum())
```

In [43]:
```python
churn_gender
```

Out[43]:

	Exited	Gender	Count	Pct
0	0	Female	3402	0.427387
1	0	Male	4558	0.572613
2	1	Female	1139	0.559156
3	1	Male	898	0.440844

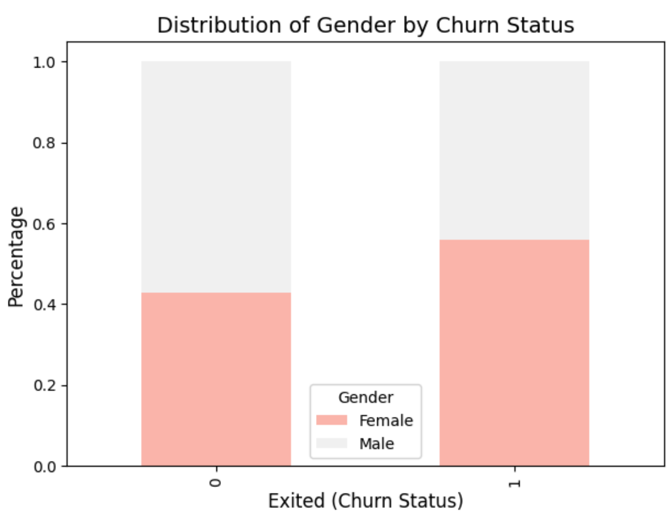
In [44]:
```python
gender_pivot = churn_gender.pivot(index='Exited', columns='Gender', values='Pct')
```

In [45]:
```python
gender_pivot
```

Out[45]:

Gender	Female	Male
Exited		
0	0.427387	0.572613
1	0.559156	0.440844

In [46]:
```python
fig, ax = plt.subplots(figsize=(7, 5))
gender_pivot.plot(kind='bar', stacked=True, ax=ax, colormap='Pastel1')
ax.set_title('Distribution of Gender by Churn Status', fontsize=14)
ax.set_xlabel('Exited (Churn Status)', fontsize=12)
ax.set_ylabel('Percentage', fontsize=12)
ax.legend(title='Gender', fontsize=10)
plt.show()
```



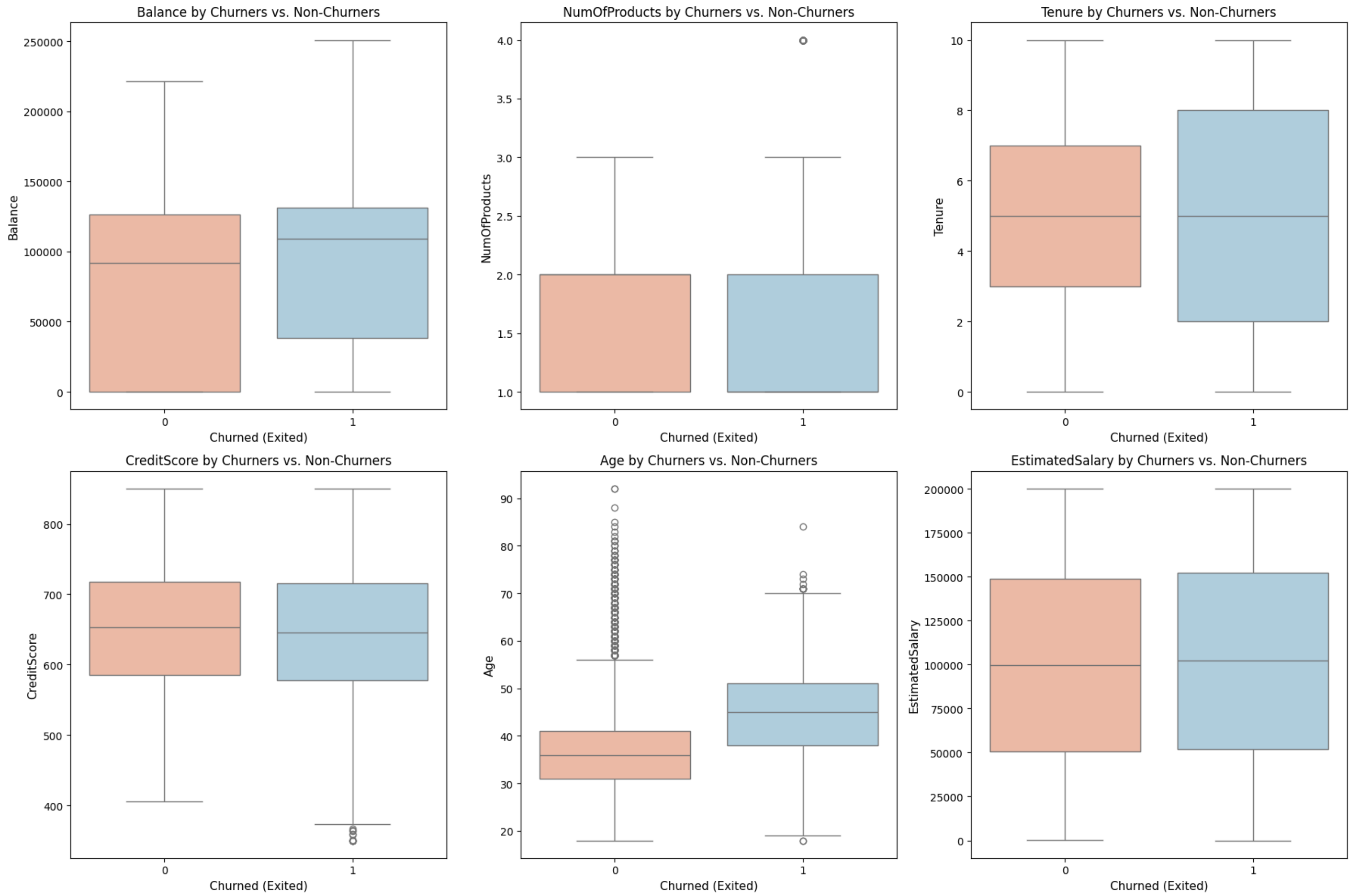
In [47]:
```python
# Build box plots for each numeric field, broken out by churners vs. non-churners
numeric_columns = ['Balance', 'NumOfProducts', 'Tenure', 'CreditScore', 'Age', 'EstimatedSalary']
```

In [48]:
```python
fig, axes = plt.subplots(2, 3, figsize=(18, 12))
axes = axes.flatten()

for i, column in enumerate(numeric_columns):
    sns.boxplot(data=df, x='Exited', y=column, palette='RdBu', hue='Exited', ax=axes[i], dodge=False, legend=False)
    axes[i].set_title(f'{column} by Churners vs. Non-Churners', fontsize=12)
    axes[i].set_xlabel('Churned (Exited)', fontsize=11)
```

```python
    axes[i].set_ylabel(column, fontsize=11)

plt.tight_layout()
plt.show()
```



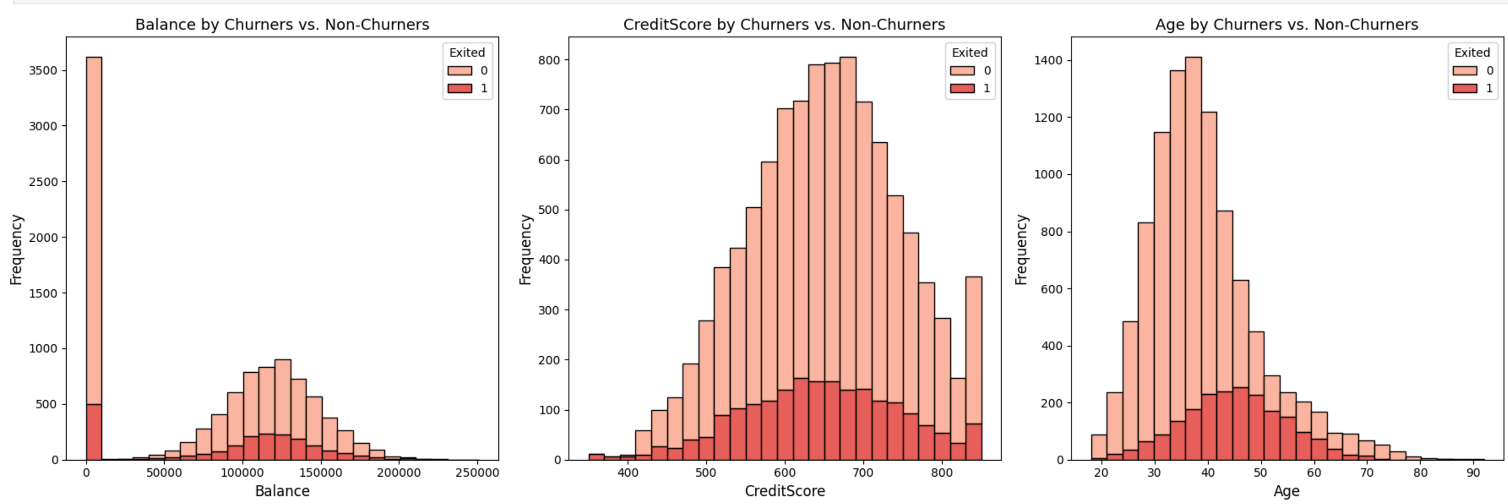
In [49]:
```python
# Build histograms for each numeric field, broken out by churners vs. non-churners
```

In [50]:
```python
numeric_columns_short = ['Balance', 'CreditScore', 'Age']

fig, axes = plt.subplots(1, 3, figsize=(18, 6))
axes = axes.flatten()

for i, column in enumerate(numeric_columns_short):
    sns.histplot(data=df, x=column, hue='Exited', multiple='stack', palette='Reds', ax=axes[i], kde=False, bins=25)
    axes[i].set_title(f'{column} by Churners vs. Non-Churners', fontsize=13)
    axes[i].set_xlabel(column, fontsize=12)
    axes[i].set_ylabel('Frequency', fontsize=12)

plt.tight_layout()
plt.show()
```



In [51]:
```python
# Objective 4
# Prepare the data for modeling
# Your final objective is to prepare the data for modeling through feature selection, feature engineering, and data splitting.
```

In [52]:
```python
# Create a new dataset that excludes any columns that aren't be suitable for modeling
```

In [53]:
```python
df
```

Out[53]:

	CustomerId	Balance	NumOfProducts	HasCrCard	Tenure	IsActiveMember	Exited	Surname	CreditScore	Geography	Gender	Age	EstimatedSalary
0	15634602	0.00	1	Yes	2	Yes	1	Hargrave	619	France	Female	42	101348.88
1	15647311	83807.86	1	Yes	1	Yes	0	Hill	608	Spain	Female	41	112542.58
2	15619304	159660.80	3	No	8	No	1	Onio	502	France	Female	42	113931.57
3	15701354	0.00	2	No	1	No	0	Boni	699	France	Female	39	93826.63
4	15737888	125510.82	1	Yes	2	Yes	0	Mitchell	850	Spain	Female	43	79084.10
...	...	...	...	...	...	...	...	...	...	...	...	...	...
9992	15606229	0.00	2	No	5	No	0	Obijiaku	771	France	Male	39	96270.64
9993	15569892	57369.61	1	Yes	10	Yes	0	Johnstone	516	France	Male	35	101699.77
9994	15584532	0.00	1	Yes	7	Yes	1	Liu	709	France	Female	36	42085.58
9995	15682355	75075.31	2	No	3	No	1	Sabbatini	772	Germany	Male	42	92888.52
9996	15628319	130142.79	1	No	4	No	0	Walker	792	France	Female	28	38190.78

9997 rows × 13 columns

In [54]:
```
model_df = df.drop(['CustomerId', 'Surname'], axis=1)
```

In [55]:
```
model_df
```

Out[55]:

	Balance	NumOfProducts	HasCrCard	Tenure	IsActiveMember	Exited	CreditScore	Geography	Gender	Age	EstimatedSalary
0	0.00	1	Yes	2	Yes	1	619	France	Female	42	101348.88
1	83807.86	1	Yes	1	Yes	0	608	Spain	Female	41	112542.58
2	159660.80	3	No	8	No	1	502	France	Female	42	113931.57
3	0.00	2	No	1	No	0	699	France	Female	39	93826.63
4	125510.82	1	Yes	2	Yes	0	850	Spain	Female	43	79084.10
...	...	...	...	...	...	...	...	...	...	...	...
9992	0.00	2	No	5	No	0	771	France	Male	39	96270.64
9993	57369.61	1	Yes	10	Yes	0	516	France	Male	35	101699.77
9994	0.00	1	Yes	7	Yes	1	709	France	Female	36	42085.58
9995	75075.31	2	No	3	No	1	772	Germany	Male	42	92888.52
9996	130142.79	1	No	4	No	0	792	France	Female	28	38190.78

9997 rows × 11 columns

In [56]:
```
# Create dummy variables for categorical fields
```

In [57]:
```
categorical_col = ['HasCrCard', 'IsActiveMember', 'Geography', 'Gender']
```

In [58]:
```
model_df = pd.get_dummies(model_df, columns=categorical_col, drop_first=True, dtype=int)
```

In [59]:
```
model_df
```

Out[59]:

	Balance	NumOfProducts	Tenure	Exited	CreditScore	Age	EstimatedSalary	HasCrCard_Yes	IsActiveMember_Yes	Geography_Germany	Geography_Spain	Gender_Male
0	0.00	1	2	1	619	42	101348.88	1	1	0	0	0
1	83807.86	1	1	0	608	41	112542.58	1	1	0	1	0
2	159660.80	3	8	1	502	42	113931.57	0	0	0	0	0
3	0.00	2	1	0	699	39	93826.63	0	0	0	0	0
4	125510.82	1	2	0	850	43	79084.10	1	1	0	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...
9992	0.00	2	5	0	771	39	96270.64	0	0	0	0	1
9993	57369.61	1	10	0	516	35	101699.77	1	1	0	0	1
9994	0.00	1	7	1	709	36	42085.58	1	1	0	0	0
9995	75075.31	2	3	1	772	42	92888.52	0	0	1	0	1
9996	130142.79	1	4	0	792	28	38190.78	0	0	0	0	0

9997 rows × 12 columns

In [60]:
```
# Create a new “balance_v_income” feature, which divides a customer’s bank balance by their estimated salary,
# then visualize that feature vs. churn status
```

In [61]:
```
model_df['balance_v_income'] = model_df.Balance / model_df.EstimatedSalary
```

In [62]:
```
model_df
```

Out[62]:

	Balance	NumOfProducts	Tenure	Exited	CreditScore	Age	EstimatedSalary	HasCrCard_Yes	IsActiveMember_Yes	Geography_Germany	Geography_Spain	Gender_Male	balance_v_income
0	0.00	1	2	1	619	42	101348.88	1	1	0	0	0	0.000000
1	83807.86	1	1	0	608	41	112542.58	1	1	0	1	0	0.744677
2	159660.80	3	8	1	502	42	113931.57	0	0	0	0	0	1.401375
3	0.00	2	1	0	699	39	93826.63	0	0	0	0	0	0.000000
4	125510.82	1	2	0	850	43	79084.10	1	1	0	1	0	1.587055
...	...	...	...	...	...	...	...	...	...	...	...	...	...
9992	0.00	2	5	0	771	39	96270.64	0	0	0	0	1	0.000000
9993	57369.61	1	10	0	516	35	101699.77	1	1	0	0	1	0.564108
9994	0.00	1	7	1	709	36	42085.58	1	1	0	0	0	0.000000
9995	75075.31	2	3	1	772	42	92888.52	0	0	1	0	1	0.808230
9996	130142.79	1	4	0	792	28	38190.78	0	0	0	0	0	3.407702

9997 rows × 13 columns

In [63]:

```
model_df = model_df[['Exited', 'Balance', 'NumOfProducts',
                     'Tenure', 'CreditScore', 'Age',
                     'EstimatedSalary', 'balance_v_income', 'HasCrCard_Yes',
                     'IsActiveMember_Yes', 'Geography_Germany', 'Geography_Spain',
                     'Gender_Male']]

model_df.columns = model_df.columns.str.lower()
```

In [64]:

```
# the final dataframe that is ready to be input into a model!
model_df
```

Out[64]:

	exited	balance	numofproducts	tenure	creditscore	age	estimatedsalary	balance_v_income	hascrcard_yes	isactivemember_yes	geography_germany	geography_spain	gender_male
0	1	0.00	1	2	619	42	101348.88	0.000000	1	1	0	0	0
1	0	83807.86	1	1	608	41	112542.58	0.744677	1	1	0	1	0
2	1	159660.80	3	8	502	42	113931.57	1.401375	0	0	0	0	0
3	0	0.00	2	1	699	39	93826.63	0.000000	0	0	0	0	0
4	0	125510.82	1	2	850	43	79084.10	1.587055	1	1	0	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
9992	0	0.00	2	5	771	39	96270.64	0.000000	0	0	0	0	1
9993	0	57369.61	1	10	516	35	101699.77	0.564108	1	1	0	0	1
9994	1	0.00	1	7	709	36	42085.58	0.000000	1	1	0	0	0
9995	1	75075.31	2	3	772	42	92888.52	0.808230	0	0	1	0	1
9996	0	130142.79	1	4	792	28	38190.78	3.407702	0	0	0	0	0

9997 rows × 13 columns