🎯 Theory: Encoding Numerical to Categorical Data

In data preprocessing, we often talk about **converting categorical data into numbers** (e.g., via one-hot or label encoding). But sometimes, we also need to do the **reverse**:

> **"Encoding numerical data as categorical"** means **converting continuous or discrete numbers into meaningful categories or groups**.

🔁 Why Convert Numerical to Categorical?

1. **Improve model interpretability** E.g., instead of using exact ages, group into "Child", "Adult", "Senior".
2. **Handle non-linear relationships** Some models (like decision trees) perform better when numeric variables are grouped.
3. **Domain knowledge** E.g., Income brackets: `<30k`, `30k-60k`, `>60k`.

🧠 How to Convert?

✅ 1. **Binning / Bucketing**

Divide a numerical range into fixed intervals.

- `pandas.cut()` → equal-width bins
- `pandas.qcut()` → equal-frequency bins (quantiles)

```
pd.cut(df['Age'], bins=[0, 18, 60, 100], labels=['Child', 'Adult', 'Senior'])
```

✅ 2. **Custom Mapping**

Based on domain logic:

```
def age_group(age):
    if age < 18:
        return 'Child'
    elif age < 60:
        return 'Adult'
    else:
        return 'Senior'

df['Age_Group'] = df['Age'].apply(age_group)
```

✅ 3. **Quantile-based Categories**

Automatically splits based on percentiles (e.g., quartiles):

```
pd.qcut(df['Income'], q=4, labels=['Low', 'Mid', 'High', 'Very High'])
```

```
Start coding or generate with AI.
```

Encoding Numerical to Categorical Data: Theory & Methods

Numerical data can be converted into categorical data (bins, groups, or labels) for better analysis, visualization, or modeling. This process is called **numerical-to-categorical encoding** or **discretization**.

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1. Why Convert Numerical to Categorical?

- **Simplification**: Easier interpretation (e.g., "Young", "Middle-aged", "Senior" instead of exact ages).
- **Handling non-linear relationships**: Some ML models (e.g., Decision Trees) work better with categories.
- **Reduce noise**: Binning smooths out fluctuations in continuous data.
- **Privacy**: Hiding exact values (e.g., income ranges instead of exact salaries).

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2. Common Techniques for Discretization

(1) Equal-Width Binning (Uniform Binning)

- Divides data into **equal-sized intervals**.
- Formula:
  $$\text{Bin width} = \frac{\text{Max value} - \text{Min value}}{\text{Number of bins}}$$
- **Example**:
  - Data: `[10, 20, 30, 40, 50, 60, 70, 80, 90, 100]`
  - Bins: `[10-30), [30-50), [50-70), [70-90), [90-110]`
  - Labels: `["Low", "Medium", "High", "Very High"]`

(2) Equal-Frequency Binning (Quantile Binning)

- Divides data into bins with **equal number of samples**.
- Uses percentiles (e.g., quartiles, deciles).
- **Example**:
  - Data: `[1, 2, 3, 4, 5, 6, 7, 8, 9, 10]`
  - 4 bins → Quartiles: `[1-3), [3-5), [5-7), [7-10]`

(3) K-Means Binning

- Uses clustering (`KMeans`) to group similar numerical values.
- Better for non-uniform distributions.

(4) Custom Binning (Domain Knowledge)

- Manually define bins based on business logic.
  - Example (Age Groups):
    - `0-18` → "Child"
    - `19-35` → "Young Adult"
    - `36-60` → "Adult"
    - `60+` → "Senior"

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3. Implementation in Python

(A) Pandas `cut()` (Equal-Width Binning)

```
import pandas as pd

data = [10, 20, 30, 40, 50, 60, 70, 80, 90, 100]
bins = [0, 30, 50, 70, 90, 110]
labels = ["Low", "Medium", "High", "Very High", "Extreme"]

df = pd.DataFrame({"Values": data})
df["Category"] = pd.cut(df["Values"], bins=bins, labels=labels)

print(df)
```

Output:

```
   Values Category
0      10      Low
1      20      Low
2      30   Medium
3      40   Medium
4      50     High
5      60     High
6      70 Very High
7      80 Very High
8      90  Extreme
9     100  Extreme
```

(B) Pandas `qcut()` (Equal-Frequency Binning)

```
df["Quantile_Bin"] = pd.qcut(df["Values"], q=4, labels=["Q1", "Q2", "Q3", "Q4"])
print(df)
```

Output:

```
   Values Quantile_Bin
0      10           Q1
1      20           Q1
2      30           Q2
3      40           Q2
4      50           Q3
5      60           Q3
6      70           Q4
7      80           Q4
8      90           Q4
9     100           Q4
```

(C) Scikit-Learn `KBinsDiscretizer`

```
from sklearn.preprocessing import KBinsDiscretizer
import numpy as np

X = np.array(data).reshape(-1, 1)
encoder = KBinsDiscretizer(n_bins=3, strategy='uniform', encode='ordinal')
df["KBins"] = encoder.fit_transform(X)

print(df)
```

Output:

```
   Values  KBins
0      10    0.0
1      20    0.0
2      30    1.0
3      40    1.0
4      50    2.0
5      60    2.0
6      70    2.0
7      80    2.0
```

```
8      90    2.0
9     100    2.0
```

---

4. Choosing the Right Method

Method	When to Use	Pros & Cons
Equal-Width (`cut`)	Uniformly distributed data	Simple, but sensitive to outliers
Equal-Freq (`qcut`)	Skewed data	Balanced bins, but may have irregular ranges
K-Means Binning	Non-linear distributions	Better clustering, but computationally heavy
Custom Binning	Domain-specific grouping (e.g., age)	Flexible, but requires manual effort

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5. Key Considerations

1. **Number of Bins**: Too few → loss of info; too many → overfitting.
2. **Outliers**: Use robust strategies (e.g., quantiles) if outliers exist.
3. **ML Impact**: Some models (e.g., linear regression) perform worse with categorical data.
4. **Ordinality**: If categories have order (e.g., "Low", "Medium", "High"), use **ordinal encoding**.

Final Thoughts

- **Use `pd.cut()` / `pd.qcut()`** for quick binning in Pandas.
- **Use `KBinsDiscretizer`** for ML pipelines.
- **Custom binning** works best when business rules are known.

```
Start coding or generate with AI.
```

Practical Implementation

our terget

- applying Decision Tree on Titanic Data set
- without Descritization and With Desctritization
- and see the changes for data

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split,cross_val_score
```

```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import FunctionTransformer,PowerTransformer,OneHotEncoder
from sklearn.impute import SimpleImputer

from sklearn.preprocessing import KBinsDiscretizer
from sklearn.pipeline import Pipeline,make_pipeline
from sklearn.tree import DecisionTreeClassifier
```

```
df=pd.read_csv('/content/Titanic-Dataset.csv')
df.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Ca
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	

```
df=df.iloc[:,[1,2,4,5,6,7,9,11]]
```

```
df.head(2)
```

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	male	22.0	1	0	7.2500	S
1	1	1	female	38.0	1	0	71.2833	C

```
from sklearn.preprocessing import Binarizer
```

```
df2=df
df2['Family']=df2['SibSp']+df2['Parch']

# df2['Family']=df2['Family'].map(lambda x: 1 if x>0 else 0) #check it instede of next 2 line c

bin=Binarizer(copy=False)
df2['Family']=bin.fit_transform(df2[['Family']])


df2=df2.drop(['SibSp','Parch'],axis=1)
df2.head(10)
```

```
<ipython-input-52-8df40fad088d>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gui
  df2['Family']=df2['SibSp']+df2['Parch']
<ipython-input-52-8df40fad088d>:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gui
  df2['Family']=bin.fit_transform(df2[['Family']])
```

	Survived	Pclass	Sex	Age	Fare	Embarked	Family
0	0	3	male	22.0	7.2500	S	1
1	1	1	female	38.0	71.2833	C	1
2	1	3	female	26.0	7.9250	S	0
3	1	1	female	35.0	53.1000	S	1
4	0	3	male	35.0	8.0500	S	0
5	0	3	male	NaN	8.4583	Q	0
6	0	1	male	54.0	51.8625	S	0
7	0	3	male	2.0	21.0750	S	1
8	1	3	female	27.0	11.1333	S	1
9	1	2	female	14.0	30.0708	C	1

```
df.head()
```

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Family
0	0	3	male	22.0	1	0	7.2500	S	1
1	1	1	female	38.0	1	0	71.2833	C	1
2	1	3	female	26.0	0	0	7.9250	S	0
3	1	1	female	35.0	1	0	53.1000	S	1
4	0	3	male	35.0	0	0	8.0500	S	0

Befor Descritization

```
X=df.drop(['Survived','Family'],axis=1)
y=df['Survived']

#corrs score: 0.78
```

```
# X=df2.drop(['Survived'],axis=1)
# y=df2['Survived']

# #0.79  (improved)
```

```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=42)
X_train.head(2)
```

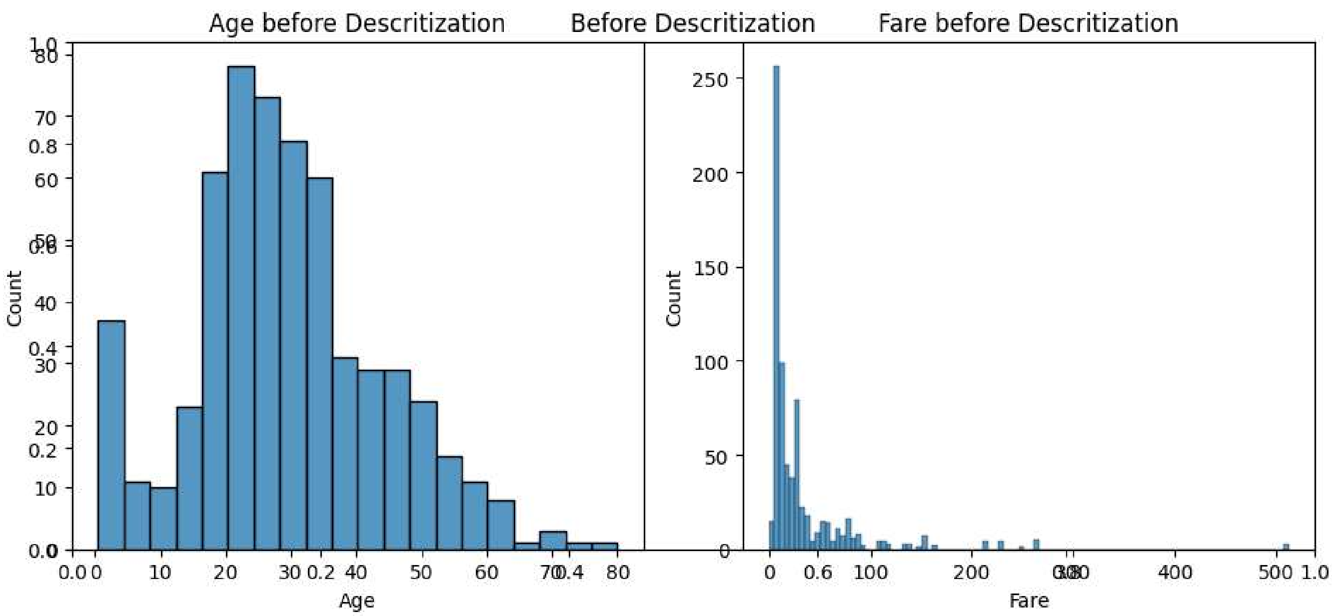
	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
331	1	male	45.5	0	0	28.5	S
733	2	male	23.0	0	0	13.0	S

EDA Befor Descritization

```
#EDA Perform
plt.figure(figsize=(10,5))
plt.title('Before Descritization')
plt.subplot(121)
sns.histplot(X_train['Age'])
plt.title('Age before Descritization')

plt.subplot(122)
sns.histplot(X_train['Fare'])
plt.title('Fare before Descritization')

plt.tight_layout()
```




```
age_pipe=Pipeline([
    ('age_imp',SimpleImputer())
])

emb_pipe=Pipeline([
    ('emb_imp',SimpleImputer(strategy='most_frequent'))
])

sex_emb_pipe=Pipeline([
        ('emb_imp',SimpleImputer(strategy='most_frequent')),
        ('ohe',OneHotEncoder(dtype=np.int32,handle_unknown='ignore',sparse_output=False))
    ])
```

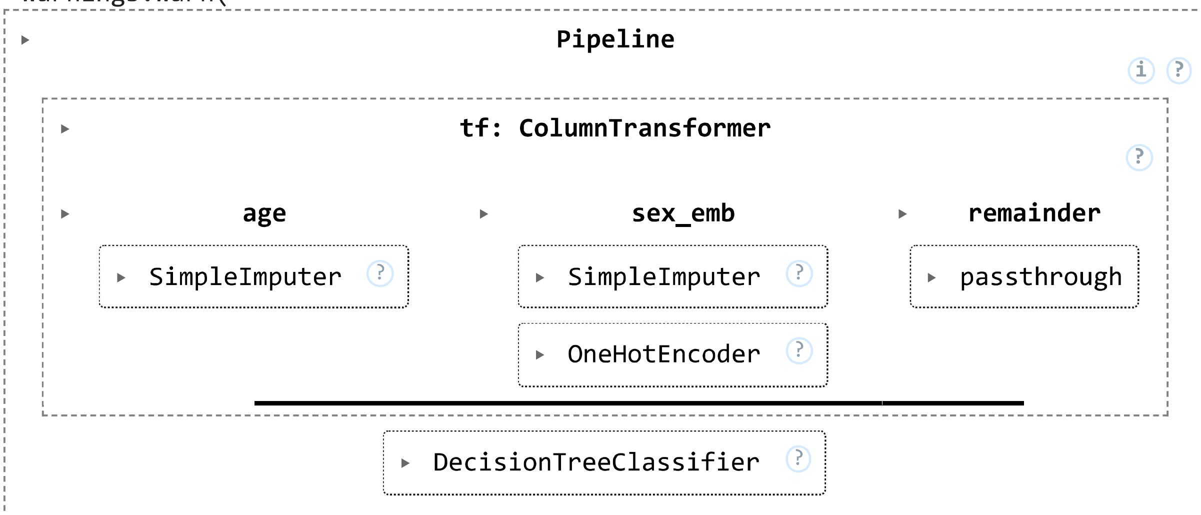
```
ct=ColumnTransformer([
    ('age',age_pipe,['Age']),
    # ('emb',emb_pipe,['Embarked']),
    ('sex_emb',sex_emb_pipe,['Sex','Embarked'])
],remainder='passthrough')

pipe_without_des=Pipeline([
    ('tf',ct),
    ('model',DecisionTreeClassifier())
])

pipe_without_des.fit(X_train,y_train)
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/compose/_column_transformer.py:1667: Future
The format of the columns of the 'remainder' transformer in ColumnTransformer.transformers_
At the moment the remainder columns are stored as indices (of type int). With the same Colu
To use the new behavior now and suppress this warning, use ColumnTransformer(force_int_rema

  warnings.warn(
```




```
y_pred=pipe_without_des.predict(X_test)
y_pred
```

```
array([0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1,
       0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1,
       0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0,
       1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0,
       0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0,
       0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0,
       0, 1, 0])
```

```
from sklearn.metrics import accuracy_score
accuracy_score(y_test,y_pred)
```

```
0.770949720670391
```

```
from sklearn.model_selection import cross_val_score
cross_val_score(pipe_without_des,X_train,y_train,cv=5,scoring='accuracy').mean()
```

```
np.float64(0.7598345316655176)
```

After Descritization(Numarical to Catagorical)

```
age_pipe=Pipeline([
    ('age_imp',SimpleImputer()),
```

```
    ('age_des',KBinsDiscretizer(n_bins=10,strategy='uniform',encode='ordinal'))
])

fare_pipe=Pipeline([
    ('fare_des',KBinsDiscretizer(n_bins=10,strategy='quantile',encode='ordinal'))
])

sex_emb_pipe=Pipeline([
        ('emb_imp',SimpleImputer(strategy='most_frequent')),
        ('ohe',OneHotEncoder(dtype=np.int32,handle_unknown='ignore',sparse_output=False))
    ])
```

```
ct2=ColumnTransformer([
    ('age',age_pipe,['Age']),
    ('fare',fare_pipe,['Fare']),
    ('sex_emb',sex_emb_pipe,['Sex','Embarked'])
],remainder='passthrough')
```

EDA After Discretisation

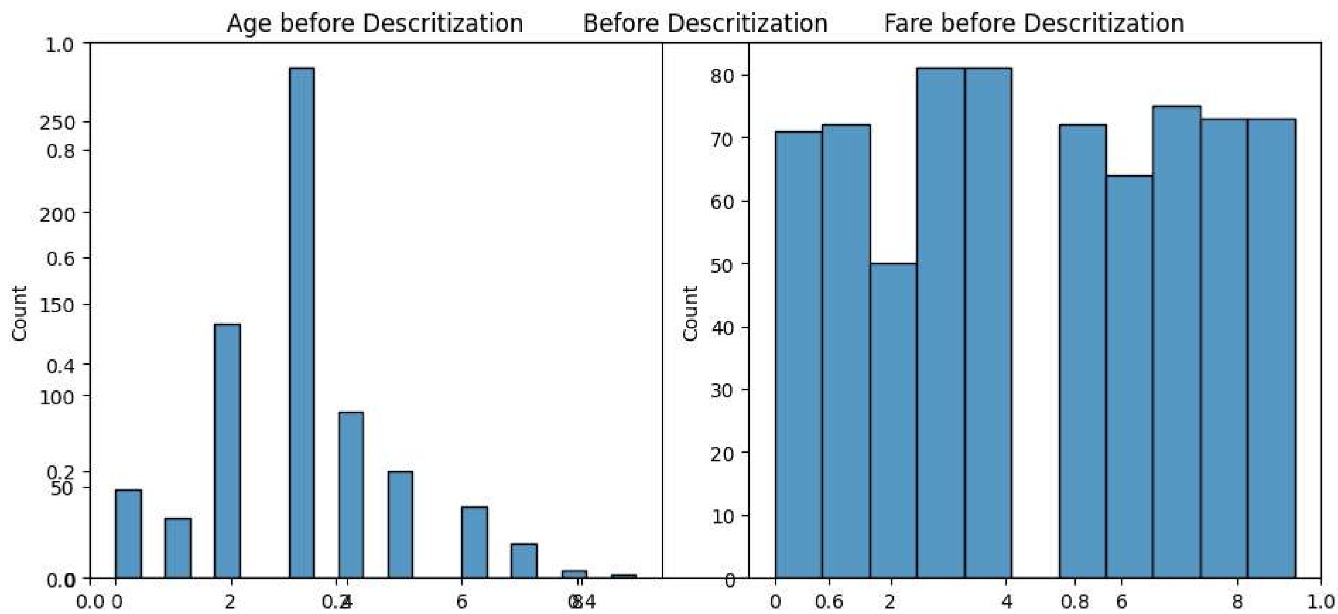
```
dzt=ct2.fit_transform(X_train)
dzt
```

```
array([[5., 7., 0., ..., 1., 0., 0.],
       [2., 4., 0., ..., 2., 0., 0.],
       [3., 2., 0., ..., 3., 0., 0.],
       ...,
       [5., 4., 0., ..., 3., 2., 0.],
       [1., 9., 1., ..., 1., 1., 2.],
       [2., 9., 0., ..., 1., 0., 1.]])
```

```
#EDA Perform
plt.figure(figsize=(10,5))
plt.title('Before Descritization')
plt.subplot(121)
sns.histplot(dzt[:,0])
plt.title('Age before Descritization')

plt.subplot(122)
sns.histplot(dzt[:,1])
plt.title('Fare before Descritization')

plt.tight_layout()
```




```
 pipe_with_des=Pipeline([
    ('tf',ct2),
    ('model',DecisionTreeClassifier())
])

pipe_with_des.fit(X_train,y_train)
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/compose/_column_transformer.py:1667: Future
The format of the columns of the 'remainder' transformer in ColumnTransformer.transformers_
At the moment the remainder columns are stored as indices (of type int). With the same Colu
To use the new behavior now and suppress this warning, use ColumnTransformer(force_int_rema

  warnings.warn(
```

Pipeline

tf: ColumnTransformer

age	**fare**	**sex_emb**
SimpleImputer	KBinsDiscretizer	SimpleImputer
KBinsDiscretizer		OneHotEncoder

DecisionTreeClassifier

```
y_pred=pipe_with_des.predict(X_test)
y_pred
```

```
array([0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1,
       0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,
       1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0,
       0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1,
       0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0,
       0, 1, 1])
```

note: After Descritization Accuracy improved

```
accuracy_score(y_pred,y_test)
```

```
0.8156424581005587
```

```
cross_val_score(pipe_with_des,X_train,y_train,cv=5,scoring='accuracy').mean()
```

```
np.float64(0.7823007977937555)
```

```
Start coding or generate with AI.
```

```
Start coding or generate with AI.
```

```
# kb=KBinsDiscretizer(n_bins=10,strategy='uniform',encode='ordinal')

# X_train['Transfrom']=kb.fit_transform(X_train[['Fare']])
# kb.bin_edges_
```

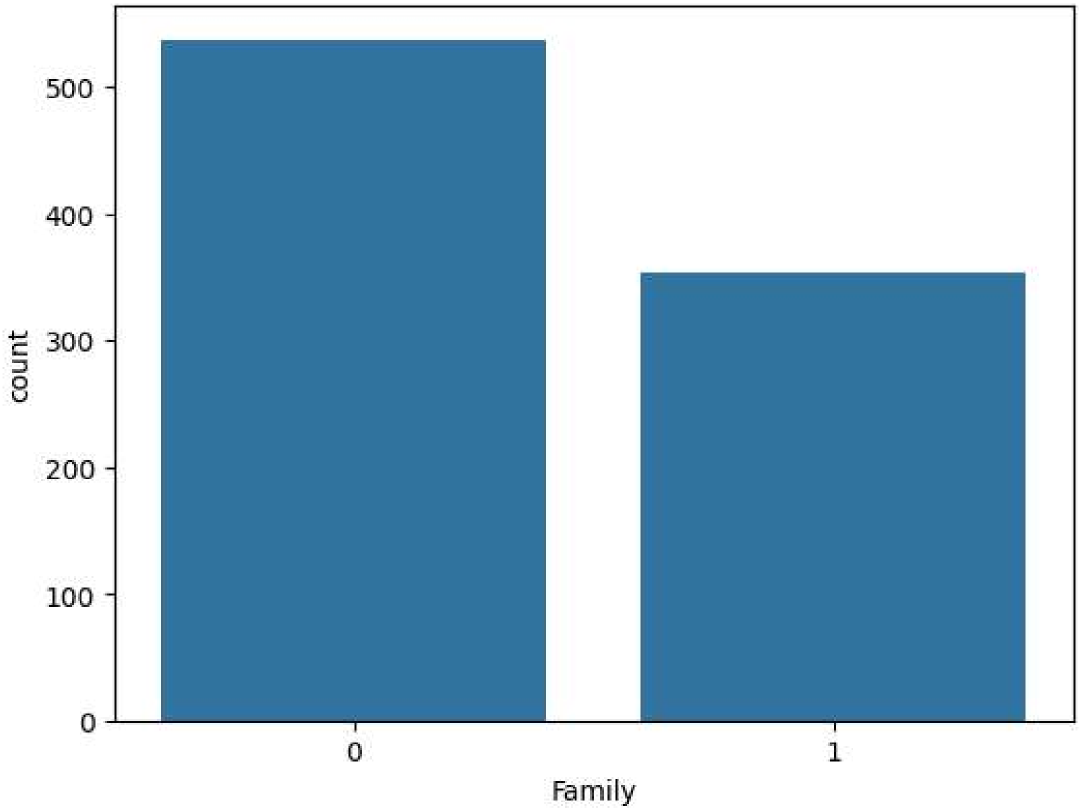
Custom Binning

```
df.head()
```

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Family
0	0	3	male	22.0	1	0	7.2500	S	1
1	1	1	female	38.0	1	0	71.2833	C	1
2	1	3	female	26.0	0	0	7.9250	S	0
3	1	1	female	35.0	1	0	53.1000	S	1
4	0	3	male	35.0	0	0	8.0500	S	0

```
sns.countplot(data=df,x='Family')
```

<Axes: xlabel='Family', ylabel='count'>




```
def rangeAge(age):
  if age<18:
    return 1
  elif age>=18 and age<=40:
    return 2
  elif age>40:
    return 3
```

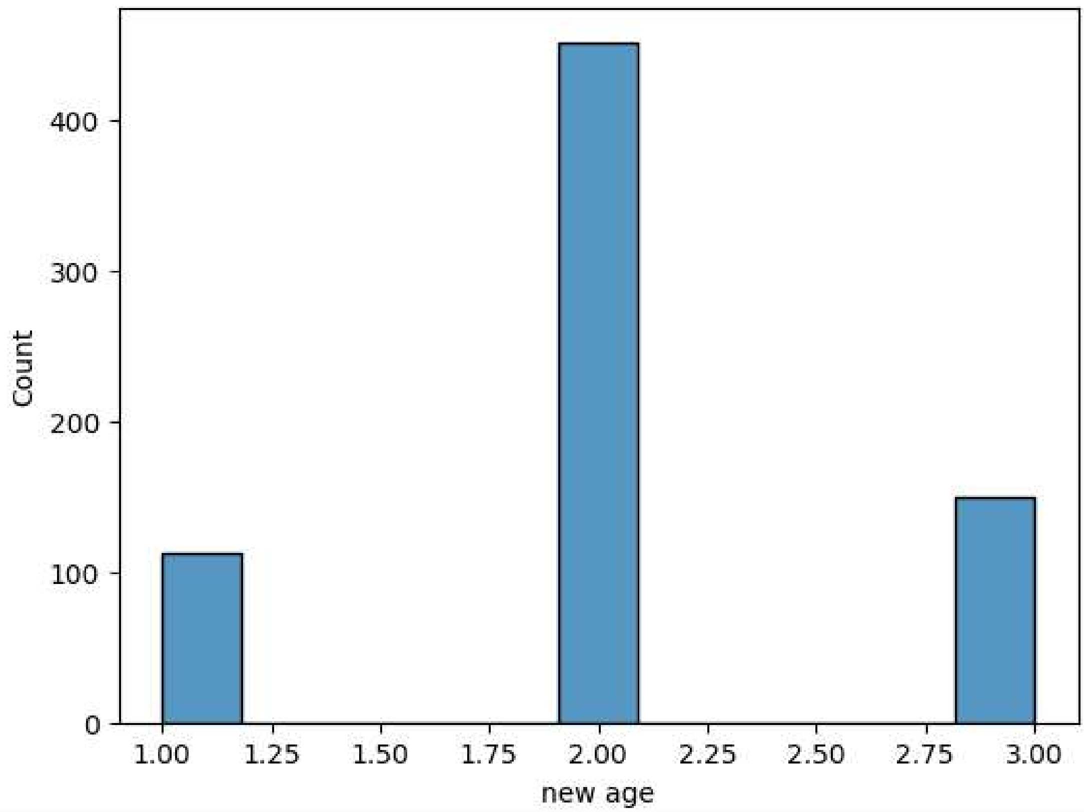
```
# df['new age']=df['Age'].map(lambda x:rangeAge(x))
df['new age']=df['Age'].apply(lambda x:rangeAge(x))
```

```
df.sample(10)
```

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Family	new age
579	1	3	male	32.0	0	0	7.9250	S	0	2.0
153	0	3	male	40.5	0	2	14.5000	S	1	3.0
251	0	3	female	29.0	1	1	10.4625	S	1	2.0
375	1	1	female	NaN	1	0	82.1708	C	1	NaN
										NaN
										NaN
										2.0
										2.0
										1.0

```
sns.histplot(data=df,x='new age')
```

```
<Axes: xlabel='new age', ylabel='Count'>
```



Start coding or generate with AI.