investor_analysis

March 28, 2025

[64]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from statsmodels.tsa.arima.model import ARIMA
import sqlite3
import warnings
warnings.filterwarnings("ignore")
```

1 Step 1: Load and Inspect Your Data

[3]:
```python
# Load dataset
df = pd.read_csv('simulated_investor_dataset.csv')
```

[4]:
```python
# Inspect the first few Rows
df.head()
```

[4]:
```
   investor_id                investor_name           investor_type  \
0         1001                 Miller-Clark                      VC
1         1002    Holmes, Arellano and Kim  Institutional Investor
2         1003             Stephens-Simmons                      VC
3         1004               Robertson-Berg                      VC
4         1005   Lawrence, Moore and Huber                      VC

     sector_fouce  check_size_usd investment_stage  investment_frequency  \
0          Edtech         6637149             Seed                    12
1              AI         5770202             Seed                     1
2         Fintech         7183366         Series B                     9
3      Healthtech         2853331         Series B                    14
4  Consumer Goods         7935478         Series C                    15

  geographic_focus last_investment_date
0             MENA           2024-05-28
```

```
1             MENA           2025-03-16
2           Europe           2024-11-30
3    North America           2025-01-16
4    North America           2024-12-26
```

[5]:
```
# check general information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 9 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   investor_id             500 non-null    int64 
 1   investor_name           500 non-null    object
 2   investor_type           500 non-null    object
 3   sector_fouce            500 non-null    object
 4   check_size_usd          500 non-null    int64 
 5   investment_stage        500 non-null    object
 6   investment_frequency    500 non-null    int64 
 7   geographic_focus        500 non-null    object
 8   last_investment_date    500 non-null    object
dtypes: int64(3), object(6)
memory usage: 35.3+ KB
```

[6]:
```
# statistical overview
df.describe(include='all')
```

[6]:
```
        investor_id investor_name investor_type sector_fouce  check_size_usd  \
count    500.000000           500           500          500    5.000000e+02
unique          NaN           490             4            8             NaN
top             NaN    Miller PLC            VC         SaaS             NaN
freq            NaN             2           136           79             NaN
mean    1250.500000           NaN           NaN          NaN    4.953943e+06
std      144.481833           NaN           NaN          NaN    2.914046e+06
min     1001.000000           NaN           NaN          NaN    1.025500e+05
25%     1125.750000           NaN           NaN          NaN    2.405582e+06
50%     1250.500000           NaN           NaN          NaN    4.945904e+06
75%     1375.250000           NaN           NaN          NaN    7.446732e+06
max     1500.000000           NaN           NaN          NaN    9.989973e+06

       investment_stage  investment_frequency geographic_focus  \
count               500            500.000000              500
unique                4                   NaN                5
top            Series C                   NaN           Europe
freq                134                   NaN              116
mean                NaN              8.140000              NaN
std                 NaN              4.403997              NaN
```

```
min                   NaN              1.000000              NaN
25%                   NaN              4.000000              NaN
50%                   NaN              8.000000              NaN
75%                   NaN             12.000000              NaN
max                   NaN             15.000000              NaN

       last_investment_date
count                   500
unique                  282
top              2024-12-10
freq                      5
mean                    NaN
std                     NaN
min                     NaN
25%                     NaN
50%                     NaN
75%                     NaN
max                     NaN
```

2 Step 2: Data Cleaning and Preprocessing

[8]:
```python
# Check for missing data
df.isnull().sum()
```

[8]:
```
investor_id             0
investor_name           0
investor_type           0
sector_fouce            0
check_size_usd          0
investment_stage        0
investment_frequency    0
geographic_focus        0
last_investment_date    0
dtype: int64
```

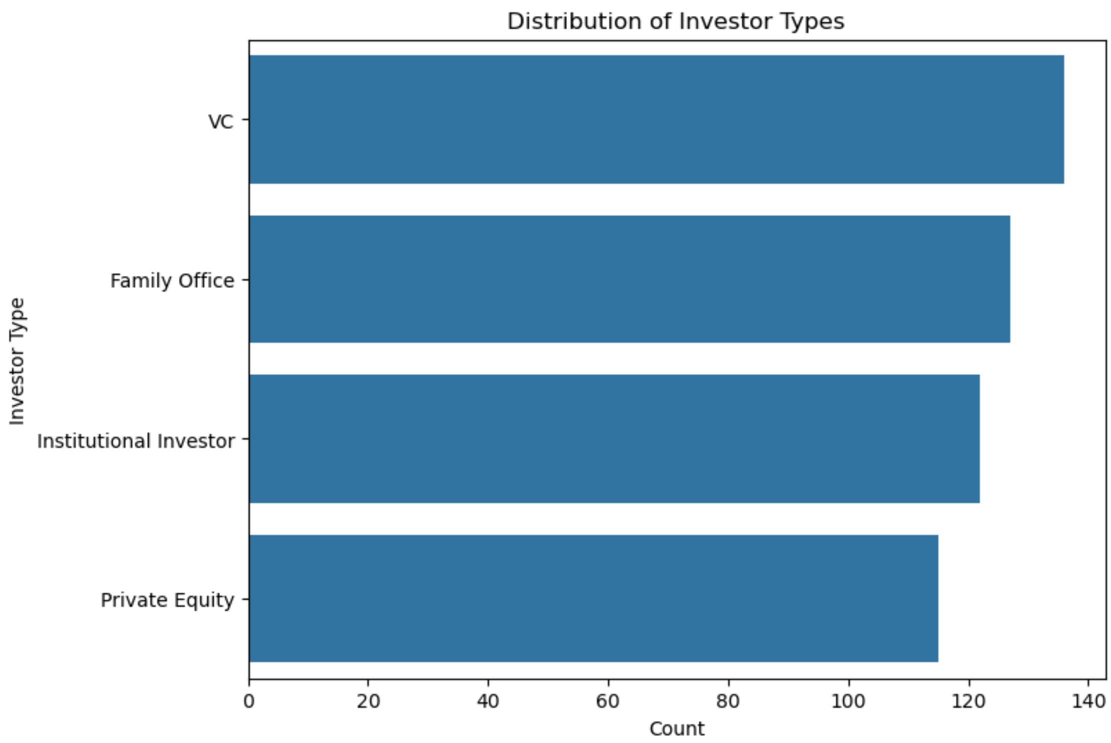
[9]:
```python
# Validate categorical variable
print(df['investor_type'].value_counts())
print(df['sector_fouce'].value_counts())
```

```
investor_type
VC                        136
Family Office             127
Institutional Investor    122
Private Equity            115
Name: count, dtype: int64
sector_fouce
SaaS                 79
```

```
Edtech             76
E-commerce         74
AI                 64
Healthtech         58
Consumer Goods     57
Fintech            49
Biotech            43
Name: count, dtype: int64
```

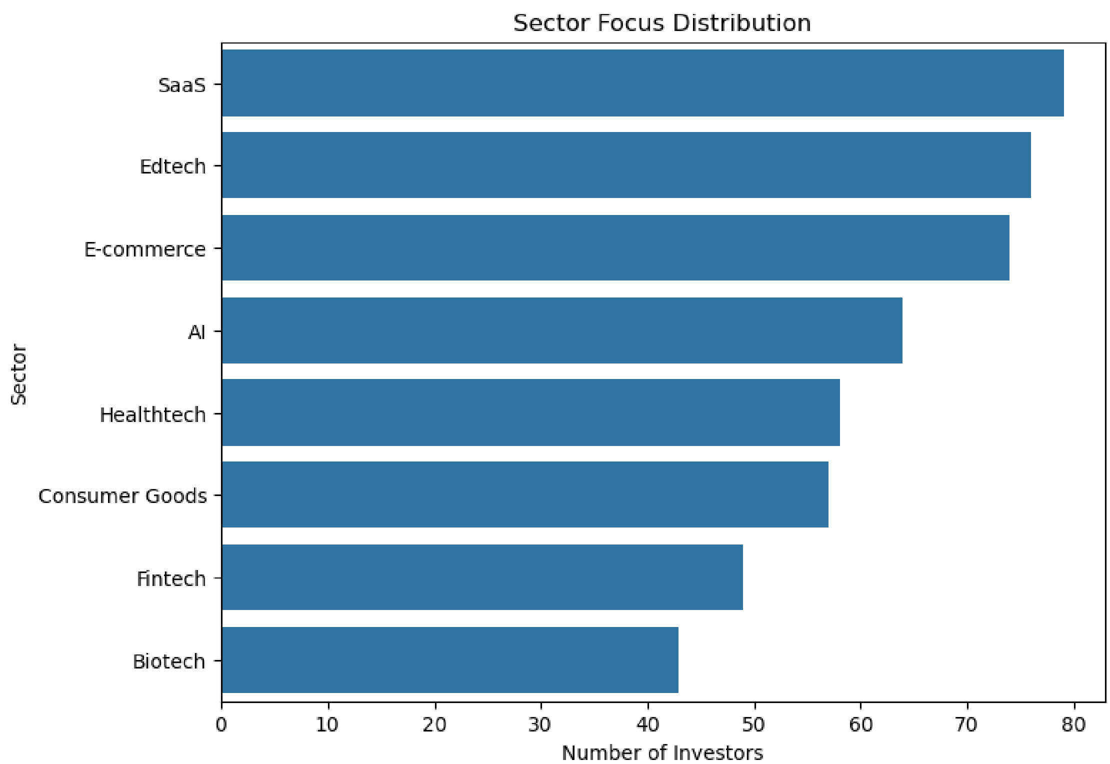
3 Step 3: Exploratory Data Analysis (EDA)

[11]:
```
# Investment patterns by investor type
plt.figure(figsize=(8,6))
sns.countplot(y='investor_type', data=df, order=df['investor_type'].
 ↪value_counts().index)
plt.title('Distribution of Investor Types')
plt.xlabel('Count')
plt.ylabel('Investor Type')
plt.show()
```

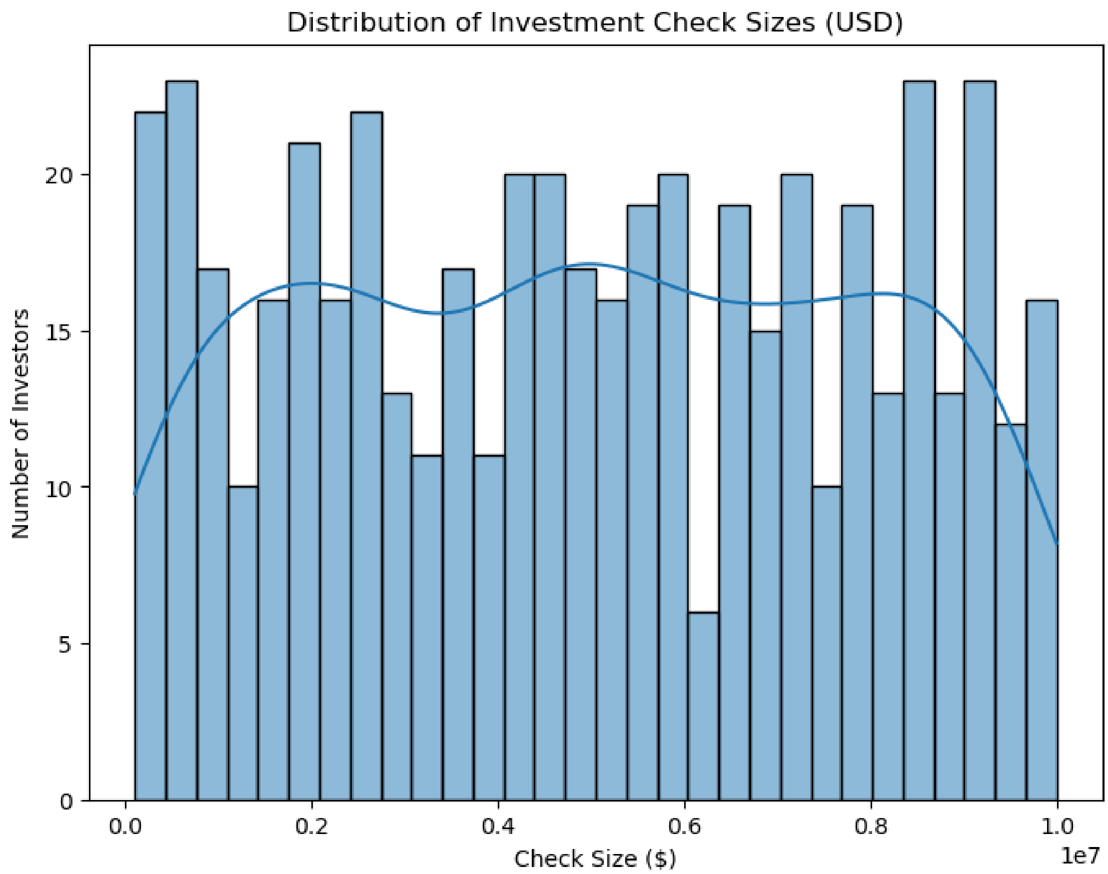


[12]:
```
# Sector Fouce analysis
plt.figure(figsize=(8,6))
```

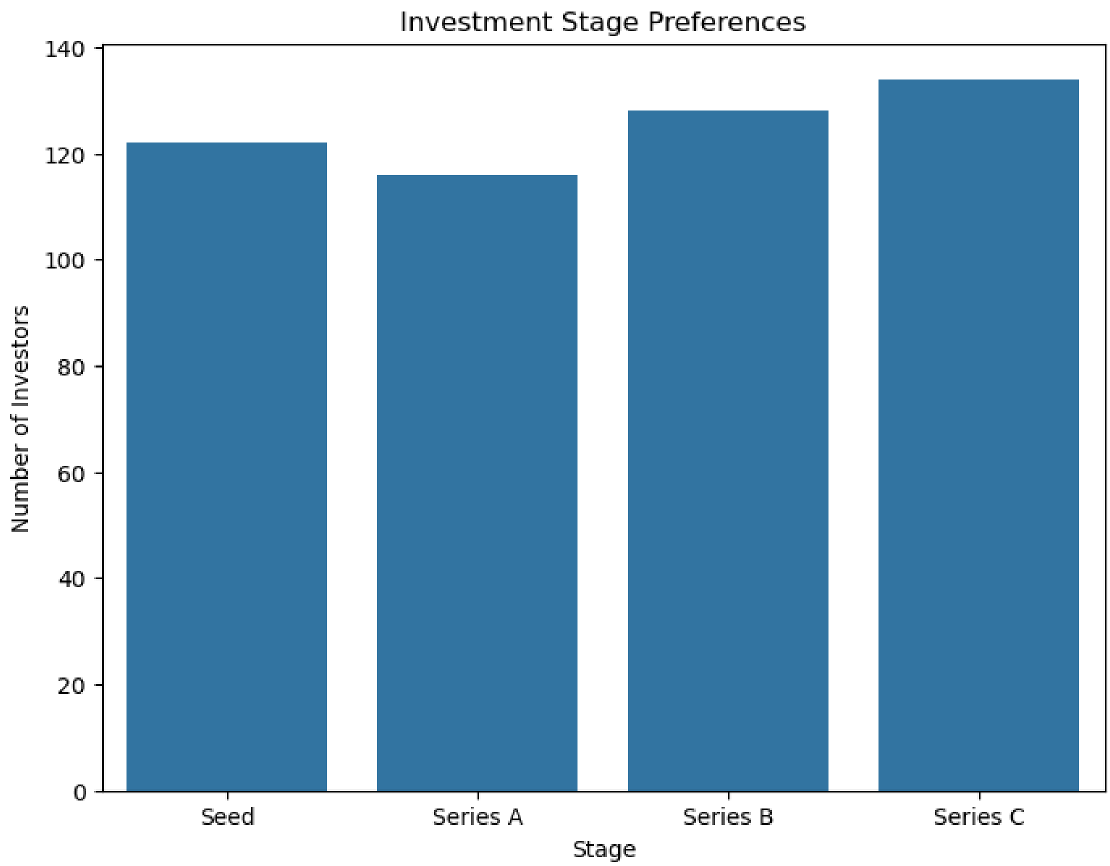
```
sns.countplot(y='sector_fouce', data=df, order=df['sector_fouce'].
 ↪value_counts().index)
plt.title('Sector Focus Distribution')
plt.xlabel('Number of Investors')
plt.ylabel('Sector')
plt.show()
```



[13]:
```
# Investment Check size analysis
plt.figure(figsize=(8,6))
sns.histplot(df['check_size_usd'], bins=30, kde=True)
plt.title('Distribution of Investment Check Sizes (USD)')
plt.xlabel('Check Size ($)')
plt.ylabel('Number of Investors')
plt.show()
```

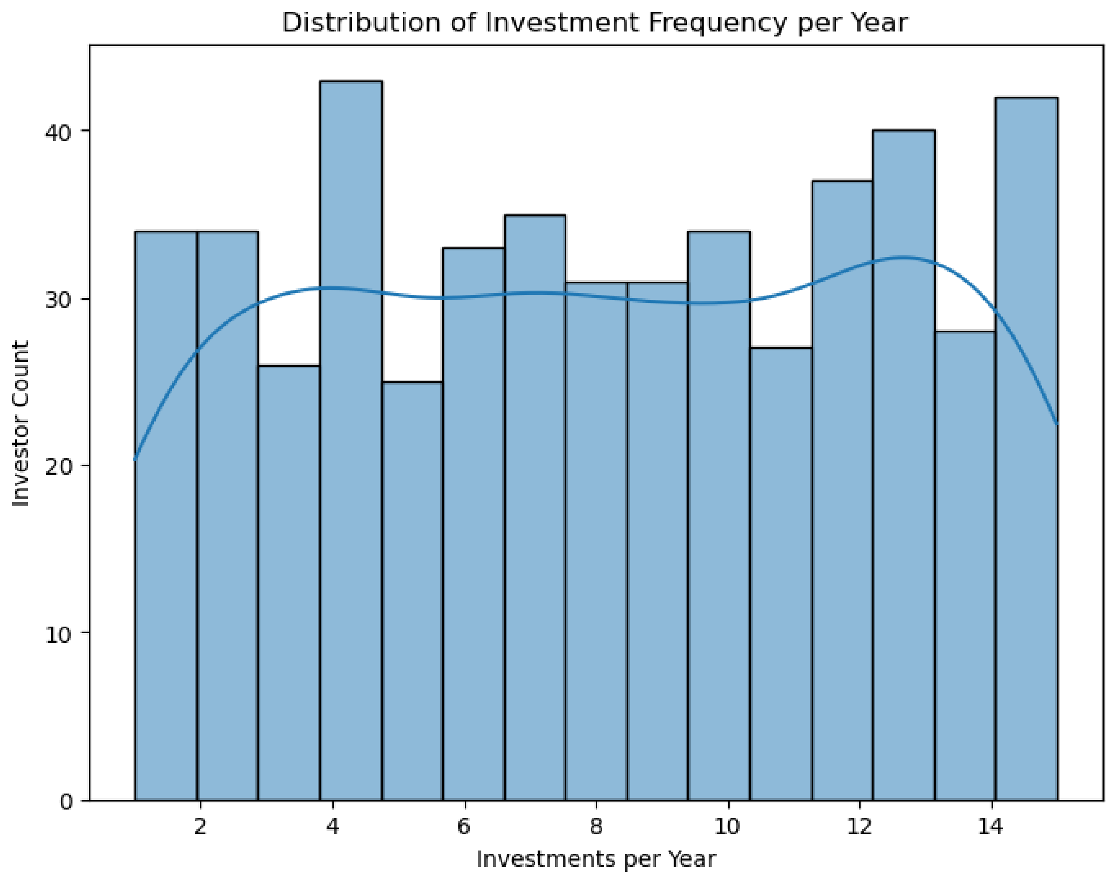


[14]:
```
# Investment stage perferences
plt.figure(figsize=(8,6))
sns.countplot(x='investment_stage', data=df, order=['Seed', 'Series A', 'Series␣
 ↪B', 'Series C'])
plt.title('Investment Stage Preferences')
plt.xlabel('Stage')
plt.ylabel('Number of Investors')
plt.show()
```

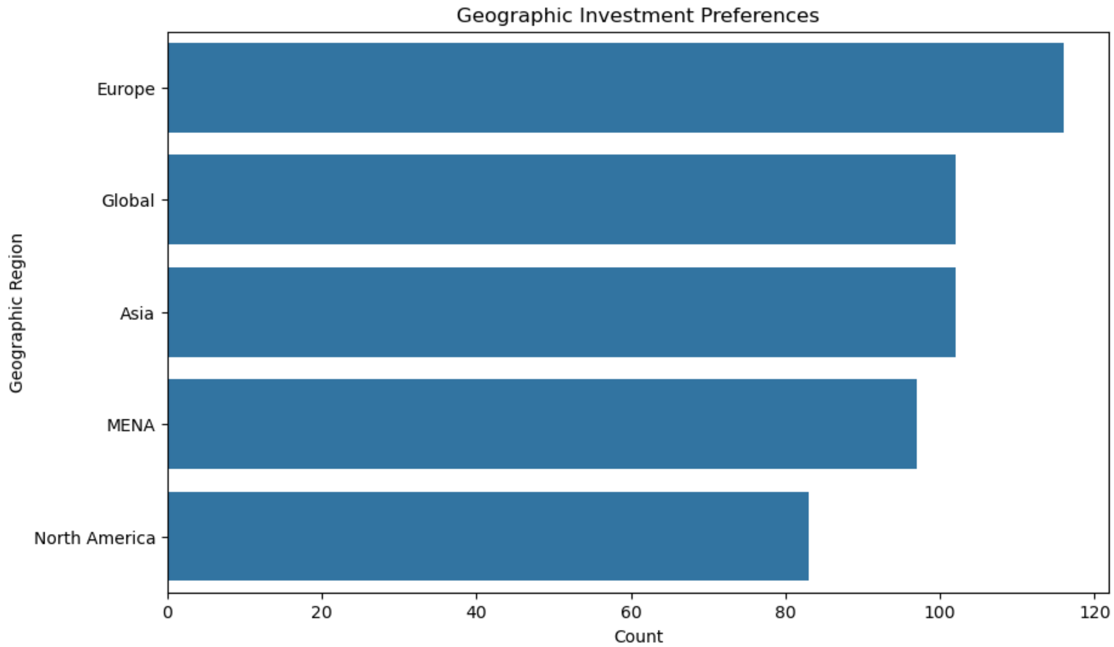


[15]:

```
# Investment Frequency Distribution
plt.figure(figsize=(8,6))
sns.histplot(df['investment_frequency'], bins=15, kde=True)
plt.title('Distribution of Investment Frequency per Year')
plt.xlabel('Investments per Year')
plt.ylabel('Investor Count')
plt.show()
```



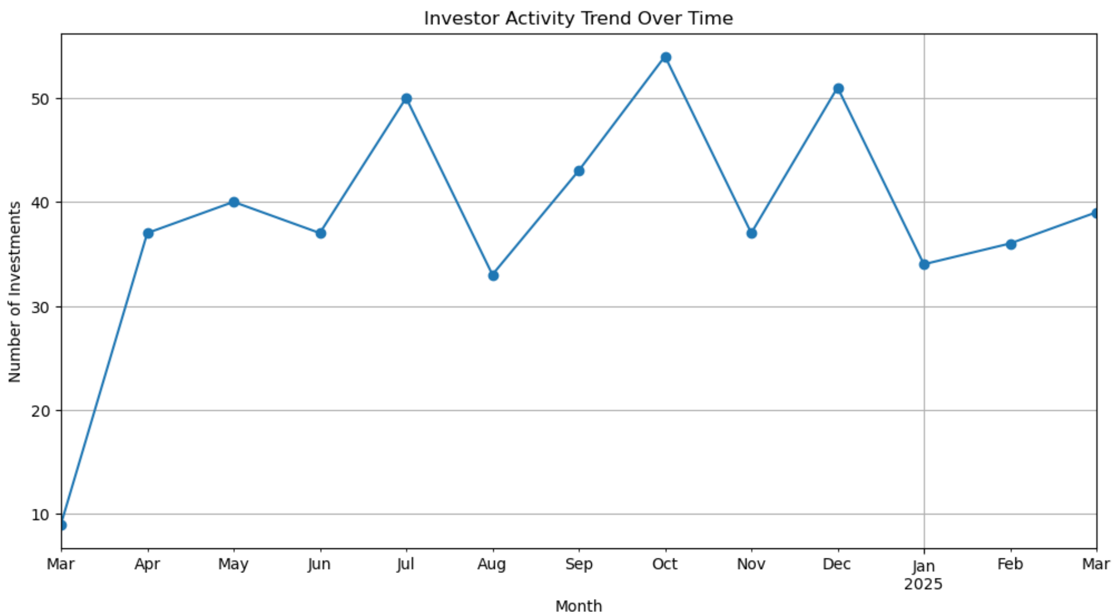
[16]:
```
# Geographic Distribution Analysis
plt.figure(figsize=(10,6))
sns.countplot(y='geographic_focus', data=df, order=df['geographic_focus'].
  ↪value_counts().index)
plt.title('Geographic Investment Preferences')
plt.xlabel('Count')
plt.ylabel('Geographic Region')
plt.show()
```



[17]:
```
# Convert 'last_investment_date' to datetime
df['last_investment_date'] = pd.to_datetime(df['last_investment_date'],␣
↪errors='coerce')
# Confirm the column is converted correctly
print(df['last_investment_date'].dtype)
```

```
datetime64[ns]
```

[18]:
```
# Investments trends over months
df['investment_month'] = df['last_investment_date'].dt.to_period('M').dt.
↪to_timestamp()
monthly_trends = df.groupby('investment_month').size()
plt.figure(figsize=(12,6))
monthly_trends.plot(marker='o')
plt.title('Investor Activity Trend Over Time')
plt.xlabel('Month')
plt.ylabel('Number of Investments')
plt.grid(True)
plt.show()
```



[19]:
```
df.rename(columns={'sector_fouce': 'sector_focus'}, inplace=True)
```

4 Investor Segmentation Using K-Means Clustering

4.1 Prepare Data for Clustering

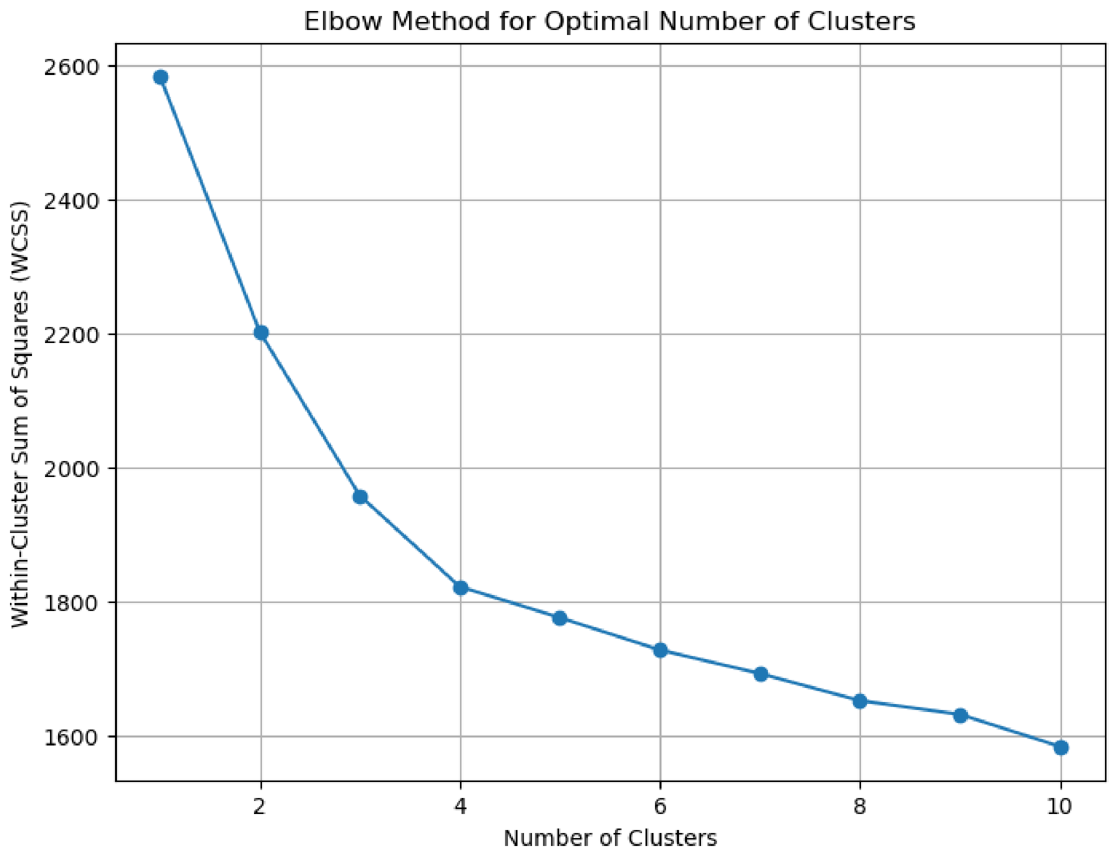
[22]:
```
# Selecting relevant features
features = ['investor_type', 'sector_focus', 'check_size_usd',␣
↪'investment_stage', 'investment_frequency', 'geographic_focus']
X = df[features]
# Preprocessing pipeline
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), ['check_size_usd', 'investment_frequency']),
        ('cat', OneHotEncoder(), ['investor_type', 'sector_focus',␣
↪'investment_stage', 'geographic_focus'])
    ])
X_processed = preprocessor.fit_transform(X)
```

4.2 Step 2: Identify the Optimal Number of Clusters (Elbow Method)

[24]:
```
# Find optimal number of clusters
wcss = []
for i in range(1,11):
    kmeans = KMeans(n_clusters=i, random_state=42, n_init=10)
    kmeans.fit(X_processed)
```

```
    wcss.append(kmeans.inertia_)
# plot the elbow curve
plt.figure(figsize=(8,6))
plt.plot(range(1, 11), wcss, marker='o')
plt.title('Elbow Method for Optimal Number of Clusters')
plt.xlabel('Number of Clusters')
plt.ylabel('Within-Cluster Sum of Squares (WCSS)')
plt.grid(True)
plt.show()
```

```
  File "C:\Users\Pc\anaconda3\Lib\site-
packages\joblib\externals\loky\backend\context.py", line 282, in
_count_physical_cores
    raise ValueError(f"found {cpu_count_physical} physical cores < 1")
```



4.3 Step 3: Apply K-Means Clustering Clearly

[26]:
```
# Apply K-means clustering
optimal_clusters = 4  # adjust based on your elbow method result
kmeans = KMeans(n_clusters=optimal_clusters, random_state=42, n_init=10)
clusters = kmeans.fit_predict(X_processed)

# Add the cluster labels to your original dataframe
df['Investor_Cluster'] = clusters
```

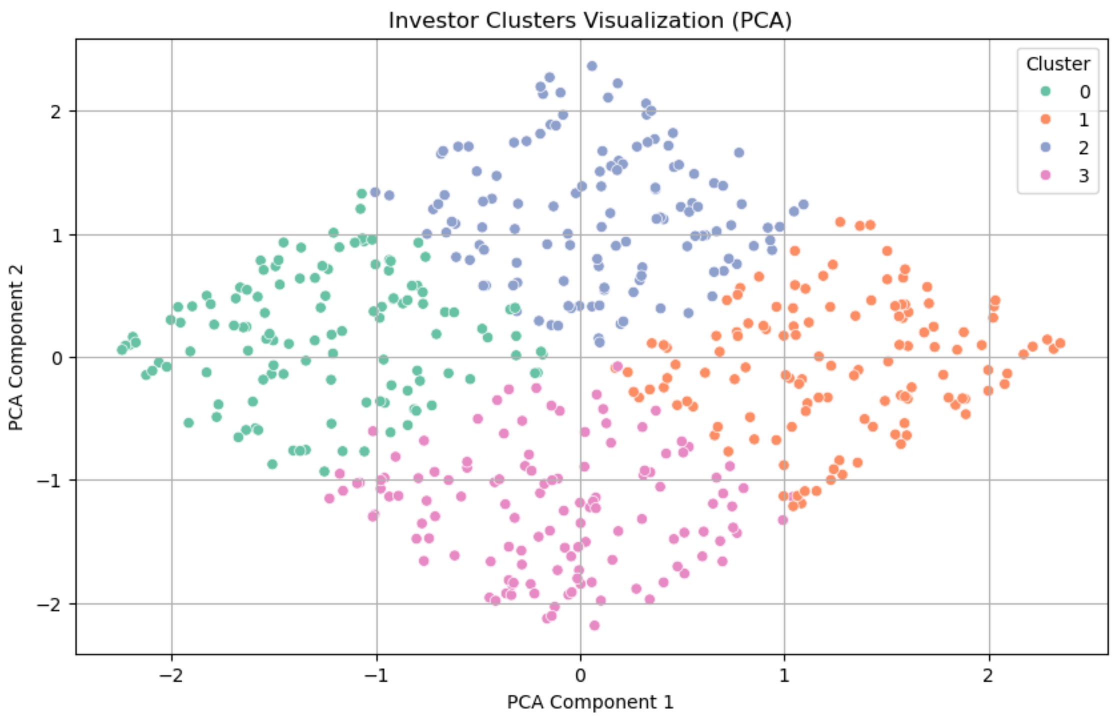
4.4 Step 4: Interpret and Analyze Clusters

[28]:
```
# Analyze cluster profiles
cluster_summary = df.groupby('Investor_Cluster').agg({
    'check_size_usd': 'mean',
    'investment_frequency': 'mean',
    'investor_type': lambda x: x.mode()[0],
    'sector_focus': lambda x: x.mode()[0],
    'investment_stage': lambda x: x.mode()[0],
    'geographic_focus': lambda x: x.mode()[0],
    'investor_id': 'count'
}).rename(columns={'investor_id': 'Number of Investors'})

print(cluster_summary)
```

```
                  check_size_usd  investment_frequency  \
Investor_Cluster
0                   2.754832e+06              3.715447
1                   7.363342e+06             12.261905
2                   7.527069e+06              4.888000
3                   2.138589e+06             11.563492

                           investor_type    sector_focus investment_stage  \
Investor_Cluster
0                         Private Equity            SaaS             Seed
1                                     VC          Edtech         Series A
2                                     VC      E-commerce         Series C
3                  Institutional Investor  Consumer Goods         Series B

                 geographic_focus  Number of Investors
Investor_Cluster
0                          Europe                  123
1                            MENA                  126
2                            Asia                  125
3                          Europe                  126
```

4.5 Step 5: Visualize Investor Clusters Clearly

[30]:
```
# Reduce dimensions for visualization
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_processed.toarray() if hasattr(X_processed,␣
↪"toarray") else X_processed)

plt.figure(figsize=(10, 6))
sns.scatterplot(x=X_pca[:, 0], y=X_pca[:, 1], hue=clusters, palette='Set2')
plt.title('Investor Clusters Visualization (PCA)')
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.legend(title='Cluster')
plt.grid(True)
plt.show()
```



5 Investor Trend Analysis (Time-Series Analysis and Forecasting)

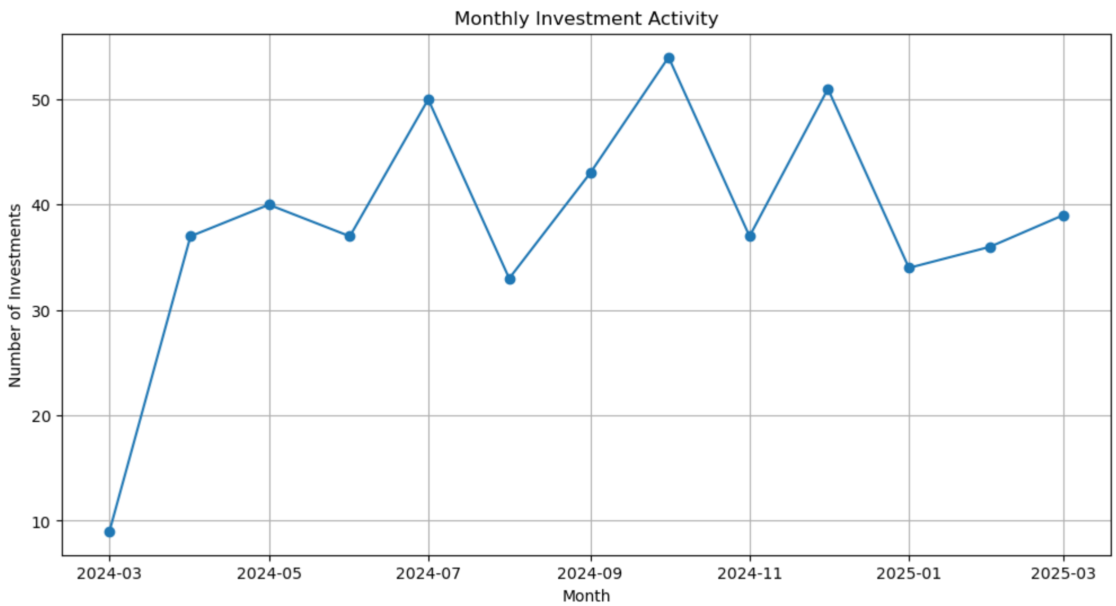
5.1 Step 1: Aggregate Data by Time

[33]:
```
# Ensure your 'investment_month' column exists and is datetime type
df['investment_month'] = pd.to_datetime(df['last_investment_date']).dt.
↪to_period('M').dt.to_timestamp()

# Count investments per month
monthly_investments = df.groupby('investment_month').size().
↪reset_index(name='number_of_investments')

# View aggregated data
print(monthly_investments.head())
```

```
  investment_month  number_of_investments
0       2024-03-01                      9
1       2024-04-01                     37
2       2024-05-01                     40
3       2024-06-01                     37
4       2024-07-01                     50
```

6 Step 2: Visualize Historical Trends

[35]:
```
plt.figure(figsize=(12, 6))
plt.plot(monthly_investments['investment_month'],␣
↪monthly_investments['number_of_investments'], marker='o')
plt.title('Monthly Investment Activity')
plt.xlabel('Month')
plt.ylabel('Number of Investments')
plt.grid(True)
plt.show()
```

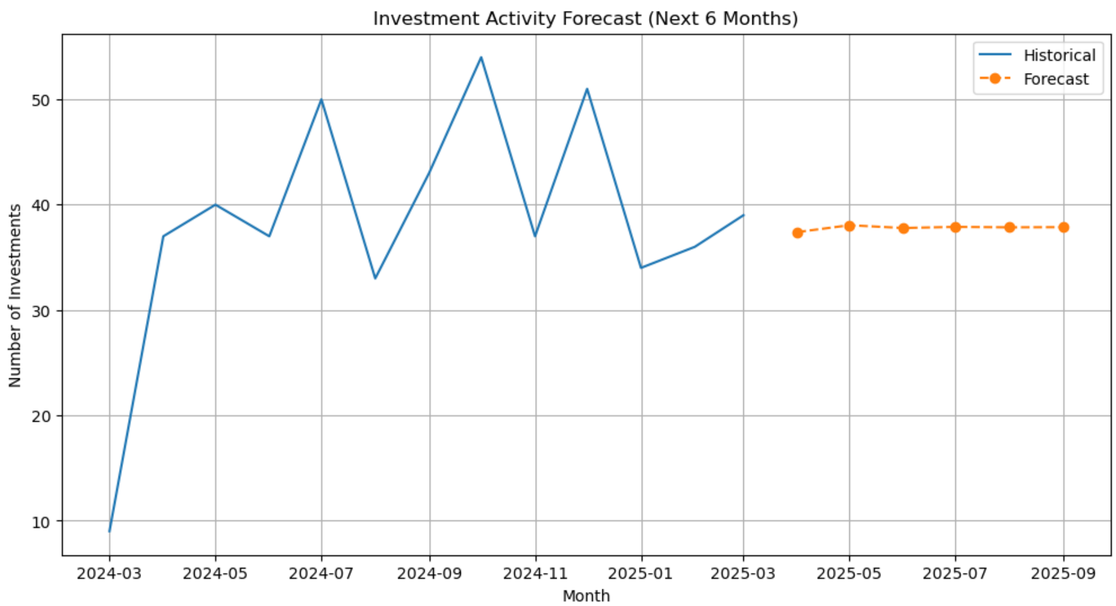


6.1 Step 3: Forecast Investor Activity (ARIMA)

[37]:
```python
# Set the 'investment_month' as index
monthly_investments.set_index('investment_month', inplace=True)

# Define and fit ARIMA model (using simple parameters initially)
model = ARIMA(monthly_investments, order=(1, 1, 1))  # ARIMA(p,d,q)
model_fit = model.fit()

# Summary of model fit
print(model_fit.summary())

# Forecast next 6 months
forecast_steps = 6
forecast = model_fit.forecast(steps=forecast_steps)

# Visualize forecast
plt.figure(figsize=(12, 6))
plt.plot(monthly_investments.index,␣
 ↪monthly_investments['number_of_investments'], label='Historical')
plt.plot(pd.date_range(start=monthly_investments.index[-1] + pd.
 ↪DateOffset(months=1), periods=forecast_steps, freq='MS'), forecast,␣
 ↪label='Forecast', marker='o', linestyle='--')
plt.title('Investment Activity Forecast (Next 6 Months)')
plt.xlabel('Month')
plt.ylabel('Number of Investments')
```

```python
plt.legend()
plt.grid(True)
plt.show()
```

```
                               SARIMAX Results
================================================================================
=
Dep. Variable:     number_of_investments   No. Observations:
13
Model:                    ARIMA(1, 1, 1)   Log Likelihood
-46.595
Date:                   Fri, 28 Mar 2025   AIC
99.191
Time:                           05:21:38   BIC
100.646
Sample:                       03-01-2024   HQIC
98.652
                            - 03-01-2025
Covariance Type:                     opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.4079      0.473     -0.862      0.389      -1.335       0.520
ma.L1         -0.3270      0.658     -0.497      0.619      -1.616       0.962
sigma2       131.9640     69.258      1.905      0.057      -3.779     267.707
================================================================================
===
Ljung-Box (L1) (Q):                   0.46   Jarque-Bera (JB):
0.99
Prob(Q):                              0.50   Prob(JB):
0.61
Heteroskedasticity (H):               0.17   Skew:
0.28
Prob(H) (two-sided):                  0.12   Kurtosis:
1.71
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
```



7 Overall Interpretation :

7.0.1 The AR and MA terms aren't statistically significant; however, that's common with limited data (only 13 months).

7.0.2 Despite this, diagnostic checks (normality, autocorrelation, heteroskedasticity) are good.

7.0.3 The model is acceptable for illustrative forecasting, though results should be treated cautiously due to limited data.

[66]:
```
# Connect to SQLite database (creates the database file automatically)
conn = sqlite3.connect('investor_crm.db')
cursor = conn.cursor()

# Create investor table clearly
cursor.execute('''
CREATE TABLE IF NOT EXISTS investors (
    investor_id INTEGER PRIMARY KEY,
    investor_name TEXT,
    investor_type TEXT,
    sector_focus TEXT,
    check_size_usd INTEGER,
    investment_stage TEXT,
    investment_frequency INTEGER,
    geographic_focus TEXT,
    last_investment_date TEXT
```

```
)
''')

conn.commit()
```

[68]:
```
# Insert DataFrame into the SQLite database clearly
df.to_sql('investors', conn, if_exists='replace', index=False)

# Check if data was inserted correctly
cursor.execute('SELECT * FROM investors LIMIT 5')
rows = cursor.fetchall()

for row in rows:
    print(row)
```

```
(1001, 'Miller-Clark', 'VC', 'Edtech', 6637149, 'Seed', 12, 'MENA', '2024-05-28
00:00:00', '2024-05-01 00:00:00', 1)
(1002, 'Holmes, Arellano and Kim', 'Institutional Investor', 'AI', 5770202,
'Seed', 1, 'MENA', '2025-03-16 00:00:00', '2025-03-01 00:00:00', 2)
(1003, 'Stephens-Simmons', 'VC', 'Fintech', 7183366, 'Series B', 9, 'Europe',
'2024-11-30 00:00:00', '2024-11-01 00:00:00', 1)
(1004, 'Robertson-Berg', 'VC', 'Healthtech', 2853331, 'Series B', 14, 'North
America', '2025-01-16 00:00:00', '2025-01-01 00:00:00', 3)
(1005, 'Lawrence, Moore and Huber', 'VC', 'Consumer Goods', 7935478, 'Series C',
15, 'North America', '2024-12-26 00:00:00', '2024-12-01 00:00:00', 1)
```

7.1 (A) Query Investors by Criteria

[71]:
```
sector = 'Fintech'
stage = 'Series A'

cursor.execute('''
SELECT investor_name, investor_type, check_size_usd, geographic_focus
FROM investors
WHERE sector_focus=? AND investment_stage=?
''', (sector, stage))

result = cursor.fetchall()

print("Fintech Series A Investors:")
for investor in result:
    print(investor)
```

```
Fintech Series A Investors:
('Ford LLC', 'Private Equity', 1284141, 'Asia')
('Collins-Carr', 'Institutional Investor', 3017857, 'Europe')
('Wright Inc', 'Institutional Investor', 1838857, 'Europe')
('Castro Ltd', 'Family Office', 4289409, 'Global')
```

```
('Henry-Woods', 'Family Office', 7896593, 'Europe')
('Santos, Cox and Riley', 'VC', 2704446, 'Asia')
('Frazier LLC', 'VC', 9044629, 'Global')
('Keller, Young and Griffin', 'Institutional Investor', 4104401, 'MENA')
('Lowery PLC', 'Private Equity', 5602146, 'Global')
('Gray, Jackson and Newman', 'Private Equity', 3030356, 'Global')
('Romero-Barajas', 'VC', 9124378, 'Europe')
```

7.2 (B) Update Investor Information

[74]:
```
investor_id = 1005  # Example ID
new_check_size = 2000000  # New check size ($2M)

cursor.execute('''
UPDATE investors
SET check_size_usd = ?
WHERE investor_id = ?
''', (new_check_size, investor_id))

conn.commit()

# Verify update clearly
cursor.execute('SELECT investor_name, check_size_usd FROM investors WHERE␣
↪investor_id=?', (investor_id,))
print(cursor.fetchone())
```

```
('Lawrence, Moore and Huber', 2000000)
```

7.3 (C) Add a New Investor Record

[77]:
```
new_investor = (1501, 'New Wave Capital', 'VC', 'AI', 5000000, 'Series B', 7,␣
↪'Europe', '2025-03-28')

cursor.execute('''
INSERT INTO investors (investor_id, investor_name, investor_type, sector_focus,␣
↪check_size_usd, investment_stage, investment_frequency, geographic_focus,␣
↪last_investment_date)
VALUES (?, ?, ?, ?, ?, ?, ?, ?, ?)
''', new_investor)

conn.commit()

# Confirm the new record
cursor.execute('SELECT * FROM investors WHERE investor_id=1501')
print(cursor.fetchone())
```

```
(1501, 'New Wave Capital', 'VC', 'AI', 5000000, 'Series B', 7, 'Europe',
'2025-03-28', None, None)
```

7.4 (D) Delete an Investor Record

[80]:
```
delete_id = 1501  # ID of investor to delete

cursor.execute('DELETE FROM investors WHERE investor_id=?', (delete_id,))
conn.commit()

# Verify deletion clearly
cursor.execute('SELECT * FROM investors WHERE investor_id=?', (delete_id,))
print(cursor.fetchone())  # Should return None
```

```
None
```

[82]:
```
conn.close()
```