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Project

Building An End To End Startup Profit Prediction ML Web Application

Team Members

Ardra P
Utkrisht Mallick
Chevulamaddi Rahul

“Artificial intelligence will reach human levels by around 2029. Follow that out further to, say, 2045, and we will have multiplied the intelligence, the human biological machine intelligence of our civilization a billion-fold.”

--Raymond ‘Ray’ Kurzweil (American author, scientist, inventor, and futurist)

1. Abstract :

Profit prediction is a crucial task for businesses, as it helps in making informed decisions and planning for the future. Machine learning (ML) models have shown great potential in predicting profits accurately, given the availability of historical data. In this project, I propose to build an ML model web application to predict profits for a given business based on its historical data. We will explore various ML algorithms such as linear regression, decision trees, gradient and adda boost models to build the model. We will also perform EDA to select the most relevant features and preprocess the data for better performance. The accuracy of the model will be evaluated using metrics such as mean squared error and R-squared. We will also perform sensitivity analysis to identify the factors that influence profit the most. The final model can be used to predict profits for new business scenarios, and the insights gained from the analysis can aid in making better business decisions.

2. Problem Statement :

Profit prediction is an essential task for businesses to ensure their financial stability and growth. Accurately predicting profits can help businesses make informed decisions, such as identifying areas for cost-cutting, increasing revenue, or investing in new projects. Traditional methods of profit prediction are often limited by human biases and lack of accuracy. Therefore, this project aims to develop a machine learning model to predict profits for a given business based on its historical data.

The problem of profit prediction can be framed as a regression task, where the goal is to predict a continuous target variable, i.e., the profit, based on several input features such as sales, marketing expenses, production costs, etc. The input features may vary depending on the type of business and the available data.

To address this problem, we will explore various machine learning algorithms, such as linear regression, decision trees, gradient and adda boost models , to build a predictive model. We will also perform feature engineering to identify and select the most relevant features, preprocess the data to handle missing values and outliers, and normalize the data for better performance. The model's accuracy will be evaluated using metrics such as mean squared error, root mean squared error, and R-squared.

The project's ultimate goal is to develop a robust machine learning model that can accurately predict profits for a given business scenario. The insights gained from the analysis can help businesses make informed decisions regarding their financial planning, investment strategies, and overall growth.

3. Market/Customer/Business Need Assessment:

Accurate profit prediction is crucial for businesses in various industries, such as retail, manufacturing, and finance. Businesses need to understand their financial performance to make informed decisions regarding their investments, cost-cutting measures, and revenue-generating strategies. Traditional methods of profit prediction may not always provide accurate results and may require significant effort and time to develop. Therefore, the need for a more accurate and efficient method of profit prediction using machine learning arises.

By using machine learning algorithms, we can build predictive models that can analyze large datasets and generate accurate profit predictions. These models can help businesses optimize their operations, identify the most profitable products or services, and plan for their financial growth. For example, in the retail industry, profit prediction can help retailers understand consumer behavior and preferences, optimize pricing strategies, and forecast sales trends.

In addition to businesses, investors, and financial analysts also require accurate profit predictions to make informed investment decisions. Profit prediction models can provide them with insights into a business's financial performance, market trends, and growth potential.

Moreover, profit prediction using machine learning can also be beneficial for startups and small businesses that may not have significant resources to invest in traditional methods of financial forecasting. Machine learning models can provide them with accurate profit predictions, enabling them to make informed decisions and plan for their financial growth.

In summary, the need for accurate profit prediction using machine learning is essential for businesses, investors, and financial analysts. The use of machine learning algorithms can provide them with accurate and efficient financial forecasting, enabling them to make informed decisions and plan for their financial growth

4. Target Specifications and Characterization:

The primary goal of this project is to develop a web application of machine learning model that can accurately predict profits for a given business scenario. To achieve this goal, the following target specifications and characterizations will be considered:

1. Accuracy: The model should be accurate in predicting profits for a given business scenario. We aim to achieve an accuracy of at least 80% on the test dataset.

2. Efficiency: The model should be efficient in terms of training time and computational resources required. We aim to develop a model that can be trained within a reasonable time frame and does not require significant computational resources.
3. Robustness: The model should be robust enough to handle missing values, outliers, and noisy data. We will perform feature engineering and data preprocessing to ensure that the model can handle such scenarios.
4. Interpretability: The model should be interpretable, meaning that we should be able to understand how the model is making predictions. This is important to gain insights into the factors that influence profits and to make informed decisions based on the model's predictions.
5. Generalizability: The model should be generalizable, meaning that it should be able to make accurate predictions for new business scenarios. We will evaluate the model's generalizability by testing it on a separate test dataset.
6. Scalability: The model should be scalable, meaning that it should be able to handle large datasets and new input features.

To achieve these target specifications and characterizations, we will explore various machine learning algorithms, perform feature engineering and data preprocessing, and evaluate the model's performance using various metrics. We will also perform sensitivity analysis to identify the factors that influence profits the most, providing insights into potential cost-cutting or revenue-generating opportunities. The final model will be a robust, accurate, and interpretable profit prediction model that can aid businesses in making informed financial decisions.

5. Online information sources/references:

Here are some websites that I used as online information sources, references, and links for profit prediction using machine learning:

1. Kaggle: Kaggle is a platform for data science competitions and provides access to a vast collection of datasets and machine learning resources. It is an excellent source for finding sample datasets and machine learning code examples related to profit prediction.
2. Towards Data Science: Towards Data Science is a community-driven platform that provides data science-related articles, tutorials, and news. It is a great source for finding articles related to machine learning and profit prediction.
3. Machine Learning Mastery: Machine Learning Mastery is a website that provides tutorials, courses, and resources related to machine learning. It is an excellent source for finding machine learning code examples related to profit prediction.
4. Analytics Vidhya: Analytics Vidhya is a platform that provides online courses, articles, and tutorials related to data science, machine learning, and AI. It is an excellent source for finding articles related to machine learning and profit prediction.
5. GitHub: GitHub is a code hosting platform for version control and collaboration. It is a great source for finding open-source machine learning code examples related to profit prediction.
6. Google Scholar: Google Scholar is a search engine that provides access to scholarly literature, including articles, theses, and conference proceedings. It is an excellent source for finding research papers related to machine learning and profit prediction.

6. Benchmarking Alternate Products for Profit Prediction Using Machine Learning:

Before starting the development of a profit prediction model using machine learning, it is important to benchmark alternate products available in the market. Benchmarking helps to identify the strengths and weaknesses of the existing products and helps in designing a better product. Here are some alternate products for profit prediction using machine learning that can be benchmarked:

1. Google Cloud AutoML: Google Cloud AutoML is a suite of machine learning tools that enables developers with limited machine learning expertise to train high-quality models specific to their business needs. It offers a drag-and-drop interface to build custom machine learning models, including those for profit prediction.
2. Microsoft Azure Machine Learning: Microsoft Azure Machine Learning is a cloud-based machine learning platform that provides a complete set of tools to build, train, and deploy machine learning models. It offers a no-code experience for building machine learning models for profit prediction.
3. Amazon SageMaker: Amazon SageMaker is a fully managed service that provides every developer and data scientist with the ability to build, train, and deploy machine learning models quickly. It offers pre-built algorithms for regression analysis and time series analysis that can be used for profit prediction.
4. H2O.ai: H2O.ai is an open-source machine learning platform that offers a suite of machine learning tools for data scientists and developers. It provides an automated machine learning platform for building machine learning models, including those for profit prediction.
5. DataRobot: DataRobot is an enterprise AI platform that automates the end-to-end process for building, deploying, and maintaining AI at scale. It offers a drag-and-drop interface to build machine learning models for profit prediction.

By benchmarking these alternate products, we can identify their strengths and weaknesses and use that knowledge to design a better profit prediction model using machine learning. We can also learn from their

7. Applicable Patents :

In general, there are many patents related to machine learning, including techniques for data preprocessing, feature selection, model selection, and hyperparameter tuning. Additionally, there may be patents related to specific algorithms, frameworks, or software used in the development of the machine learning model. It is important to conduct a thorough search to identify any applicable patents and take steps to ensure that the product or service idea does not infringe on them.

Some examples of patents related to machine learning models include:

US Patent 9,454,830: "Method and System for Training a Machine Learning Model with Clustered Loss Functions", US Patent 10,640,858: "Machine Learning Model for Predicting Outcomes of Financial Transactions", US Patent 10,743,787: "Method and System for Developing and Deploying Machine Learning Models in a Distributed Environment", US Patent 11,128,974: "Machine Learning System and Method for Predictive Maintenance" Again, it is important to note that these are just examples of patents related to machine learning models and may not be applicable to my Profit Prediction model specific technology or product idea.

8. Applicable Regulations :

The regulations applicable to profit prediction using machine learning will vary depending on the industry and location of the business. However, there are some general regulations that may be relevant to consider when developing a profit prediction model using machine learning. These include:

1. Data protection regulations: Businesses must comply with data protection regulations such as the General Data Protection Regulation (GDPR) in the EU and the California Consumer Privacy Act (CCPA) in the US. These regulations govern how businesses collect, store, and use customer data and may

require explicit consent from customers to use their data for profit prediction purposes.
2. Anti-discrimination regulations: It is important to ensure that profit prediction models do not discriminate against protected classes such as race, gender, or age. In the US, the Equal Credit Opportunity Act (ECOA) prohibits discrimination in credit decisions, while the Fair Housing Act (FHA) prohibits discrimination in housing decisions.
3. Financial regulations: If the profit prediction model is used to make financial decisions, businesses may need to comply with financial regulations such as the Dodd-Frank Wall Street Reform and Consumer Protection Act in the US.
4. Intellectual property regulations: It is important to ensure that the profit prediction model does not infringe on any existing patents or intellectual property rights.
5. Consumer protection regulations: In some industries, such as healthcare, there may be regulations governing how businesses can use customer data and make predictions about their behavior.

It is important to consult with legal and regulatory experts to ensure that the profit prediction model complies with all applicable regulations.

9. Applicable Constraints:

1. Data quality: Machine learning models rely on high-quality data to make accurate predictions. If the data used to train the model is incomplete, inconsistent, or biased, it may result in inaccurate predictions.
2. Model complexity: More complex machine learning models may be more accurate, but they may also be slower and require more computing resources. This can be a constraint for businesses with limited resources.
3. Regulatory constraints: As mentioned in my previous response, businesses must comply with various regulations when using machine learning for profit prediction. Failure to comply with these regulations can result in legal and financial consequences.
4. Transparency: Machine learning models can be difficult to interpret, and it may be challenging to understand how they arrive at their predictions. This can be a constraint in industries where transparency is important, such as healthcare.
5. Interpretability: Related to transparency, some machine learning models may be difficult to interpret and explain to stakeholders, which can be a constraint in industries where stakeholders require clear explanations for the predictions.
6. Data privacy: The use of sensitive data in profit prediction models may raise concerns about data privacy, and businesses must ensure that they are following relevant regulations and ethical considerations.

It is important to consider these constraints when developing a profit prediction machine learning model and to ensure that the model is accurate, transparent, and complies with all applicable regulations.

10. Business Opportunity:

The business opportunity for profit prediction web application using machine learning is significant. Accurately predicting future profits can help businesses make informed decisions about their operations, investments, and growth strategies. Machine learning models can analyze large amounts of data and identify patterns that may not be immediately apparent to humans, leading to more accurate predictions.

Some specific business opportunities for profit prediction web application using machine learning include:

1. Identifying opportunities for growth: Machine learning models can identify patterns and trends in customer behavior and market trends that can help businesses identify opportunities for growth and expansion.

2. Optimizing pricing strategies: Machine learning models can analyze data on customer behavior, competition, and market trends to help businesses optimize their pricing strategies and maximize profits.
3. Improving supply chain management: Machine learning models can analyze data on inventory levels, shipping times, and other factors to help businesses optimize their supply chain management and reduce costs.
4. Enhancing customer satisfaction: By accurately predicting customer behavior, businesses can tailor their products and services to meet customer needs and enhance satisfaction, leading to increased profits.
5. Streamlining operations: Machine learning models can identify inefficiencies in business operations and help businesses streamline processes to reduce costs and increase profits.

Overall, the use of machine learning for profit prediction presents a significant opportunity for businesses to increase profits, reduce costs, and make more informed decisions.

11. Business Model Can be Used:

There are several business models that businesses can use to monetize the profit prediction machine learning model.

1. Subscription model: Businesses can offer access to their profit prediction machine learning model on a subscription basis. Customers would pay a recurring fee to use the model to predict their future profits.
2. Pay-per-use model: Similar to a subscription model, businesses can charge customers on a pay-per-use basis. Customers would only pay for the predictions they need, rather than a recurring subscription fee.
3. Licensing model: Businesses can license their profit prediction machine learning model to other businesses for a fee. This would allow other businesses to use the model to predict their profits without having to develop their own model from scratch.
4. Value-added services: Businesses can offer value-added services in addition to their profit prediction machine learning model. For example, they could offer consulting services to help businesses interpret the predictions and develop strategies based on the predictions.
5. Product bundles: Businesses can bundle their profit prediction machine learning model with other products or services they offer. This could make the model more attractive to customers and increase sales of other products or services.
6. Data analysis services: Businesses can offer data analysis services using their profit prediction machine learning model. For example, they could offer to analyze a customer's data to identify trends and make predictions about future profits.

These are just a few examples of potential business models for profit prediction using machine learning. The right model will depend on the specific needs of the business and its customers.

12. Concept Generation :

1. Identify the problem: The first step is to identify the problem or opportunity that the profit prediction machine learning model web application will address. This could include improving the accuracy of profit predictions, identifying opportunities for growth, optimizing pricing strategies, or reducing costs.
2. Gather data: Once the problem has been identified, the next step is to gather the data that will be used to train the machine learning model. This may include financial data, customer data, sales data, and market data.

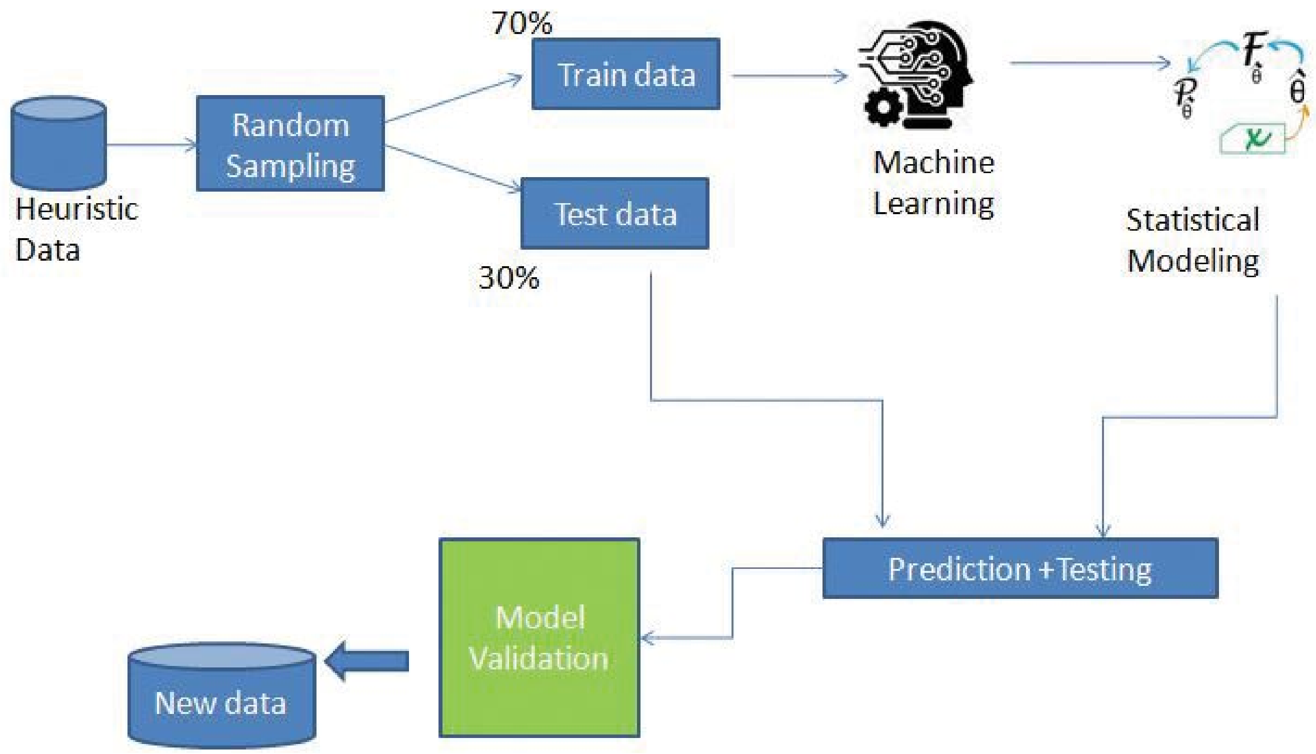
3. Define the model: Based on the problem and the data, the next step is to define the machine learning model that will be used to make profit predictions. This may include selecting the type of model, such as regression, decision trees, or adda boost and gradient boost.
4. Train the model: Once the model has been defined, it needs to be trained using the gathered data. This involves feeding the data into the model and adjusting the model's parameters to optimize its accuracy.
5. Evaluate the model: After the model has been trained, it needs to be evaluated to ensure that it is accurate and effective. This may involve testing the model on new data or comparing its predictions to actual profits.
6. Refine the model: Based on the evaluation, the model may need to be refined or adjusted to improve its accuracy. This may involve tweaking the parameters of the model, adding new data, or selecting a different type of model.
7. Implement the model: Once the model has been refined and tested, it can be implemented into a

13. Concept Development :

A profit prediction machine learning web application is a type of algorithm that uses historical data to predict future profits for a business. It leverages the power of artificial intelligence and machine learning to analyze large amounts of data, identify patterns and trends, and make accurate predictions about a business's financial performance. By using advanced algorithms and predictive modeling techniques, profit prediction machine learning models can help businesses optimize pricing strategies, identify growth opportunities, reduce costs, and make better decisions about how to allocate resources. Overall, profit prediction machine learning models are a powerful tool for businesses looking to improve their financial performance and stay ahead of the competition.

14. Final Product Prototype :

The profit prediction machine learning model is an innovative solution designed to help businesses optimize their financial performance and make data-driven decisions. Leveraging the power of artificial intelligence and machine learning, this model can analyze vast amounts of historical data, identify trends, and accurately predict future profits for a business. By providing accurate and reliable predictions, the profit prediction machine learning web application can help businesses optimize pricing strategies, identify growth opportunities, and reduce costs, ultimately driving greater profitability and competitiveness. With its advanced algorithms and predictive modeling techniques, this model is an essential tool for businesses looking to stay ahead of the competition and make smart, data-driven decisions about their financial future.



After creating the model we need to build a web application or website that can take user input and process it using the trained model. You can use any web development framework or language of your choice, such as Flask, Django, or Node.js.

Create an endpoint or API that receives user input and sends it to your machine learning model for processing. The endpoint should be able to load the trained model and use it to generate predictions or classifications.

Integrate the endpoint or API into your web application or website. This may involve creating a form for users to input data, or using AJAX requests to send data to the endpoint without refreshing the page.

Display the results of the machine learning model to the user in a way that is easy to understand and interpret. This may involve creating visualizations or charts to display the data, or simply presenting the results in a text format.

Test your web application or website to make sure it is functioning correctly and providing accurate results. You may need to adjust the machine learning model or the web application to improve performance or accuracy.

Overall, integrating a machine learning model with a website involves building an API or endpoint that can accept user input, process it using the model, and return the results to the user. This requires knowledge of both machine learning and web development, as well as an understanding of how to create user-friendly and intuitive web interfaces.

15. Product details :

1. Data Sources: The data sources for profit prediction using machine learning can include various financial and business data such as sales data, customer data, marketing data, and operational data. The data can be collected from a company's internal systems, publicly available sources, or third-party providers.
2. Algorithms, Frameworks, Software, etc. needed: The choice of algorithms, frameworks, and software will depend on the specific needs of the project. Some commonly used machine learning algorithms for profit prediction include regression analysis, decision trees, and adda boosing and gradient boosting. Frameworks such as Scikit-learn, TensorFlow, and Keras can be used for developing and training the model In this project i have used scikit-learn to train the model. Other tools such as Jupyter Notebooks, Python, and Excel can also be useful for data analysis and visualization.

   Libraries used for this project are Numpy, Pandas, Matplotlib, Seaborn and the Scikit-learn for model training and validation.

3. Team Required to Develop: The team required to develop a profit prediction machine learning model would typically include data scientists, machine learning engineers, software developers, Cloud engineer and domain experts. The size and composition of the team will depend on the scope and complexity of the project.
4. What does it cost? Web site cost, developing cost, maintaning cost. The cost of developing a profit prediction machine learning model web appication will depend on various factors such as the complexity of the project, the size of the data, the tools and technologies used, and the size of the development team. However, it is generally expected to be a substantial investment. Other costs to consider include ongoing maintenance, data storage, and any third-party services needed to collect and process the data.

16. Code Implementation:

The dataset that I am using for the task of profit prediction includes data about the R&D spend, Administration cost, Marketing Spend, State of operation, and the historical profit generated by 50 startups. So let’s start with the task of profit prediction by importing the necessary Python libraries and the dataset:

In [27]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set()
import warnings
warnings.filterwarnings('ignore')
from sklearn.linear_model import LinearRegression
```

In [28]:

```python
df=pd.read_csv("Profit_Analys.csv")
df.head(7)
```

Out[28]:

	R&D Spend	Administration	Marketing Spend	State	Profit
0	165349.20	136897.80	471784.10	New York	192261.83
1	162597.70	151377.59	443898.53	California	191792.06
2	153441.51	101145.55	407934.54	Florida	191050.39
3	144372.41	118671.85	383199.62	New York	182901.99
4	142107.34	91391.77	366168.42	Florida	166187.94
5	131876.90	99814.71	362861.36	New York	156991.12
6	134615.46	147198.87	127716.82	California	156122.51

In [29]:

```python
df.describe().T
```

Out[29]:

	count	mean	std	min	25%	50%	
R&D Spend	50.0	74093.9776	45353.030380	0.00	39936.3700	73051.080	10160
Administration	50.0	120311.6446	28437.137663	51283.14	100147.4200	122107.195	14484
Marketing Spend	50.0	212020.5446	120633.691805	0.00	135028.2075	212716.240	29946
Profit	50.0	112764.7870	38579.913636	35673.41	83409.0800	107978.190	13976

In [30]:

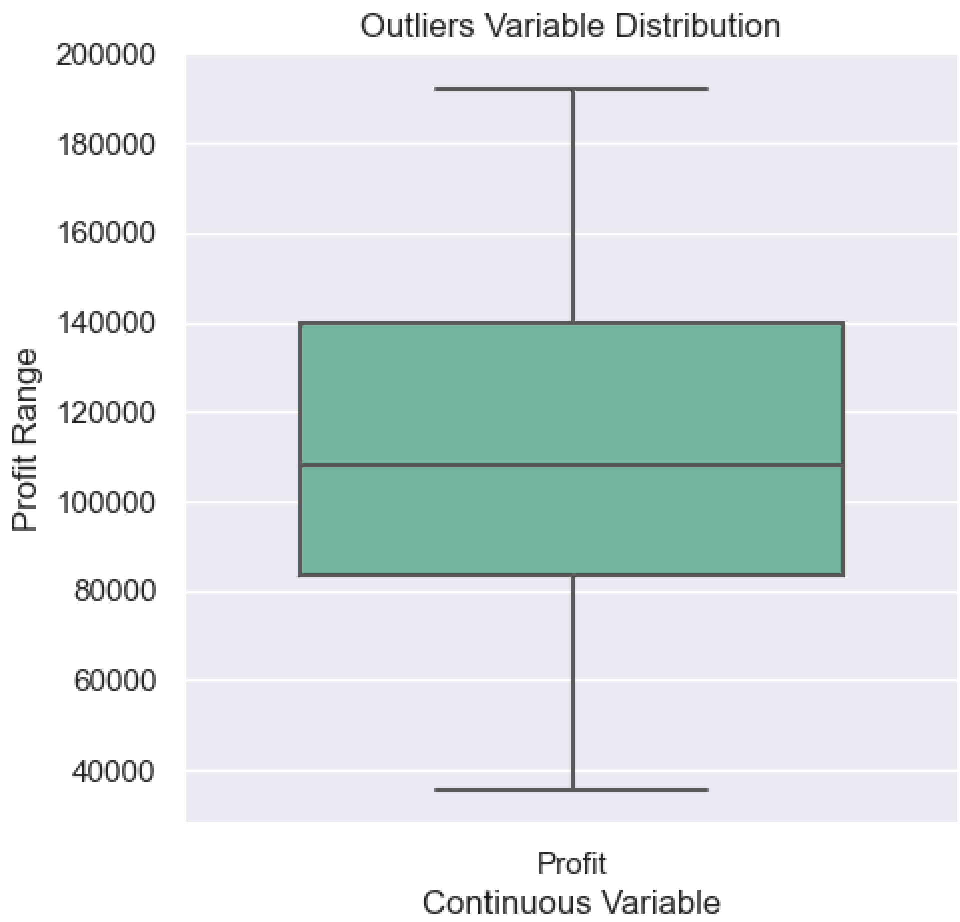
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   R&D Spend        50 non-null     float64
 1   Administration   50 non-null     float64
 2   Marketing Spend  50 non-null     float64
 3   State            50 non-null     object 
 4   Profit           50 non-null     float64
dtypes: float64(4), object(1)
memory usage: 2.1+ KB
```

In [31]:

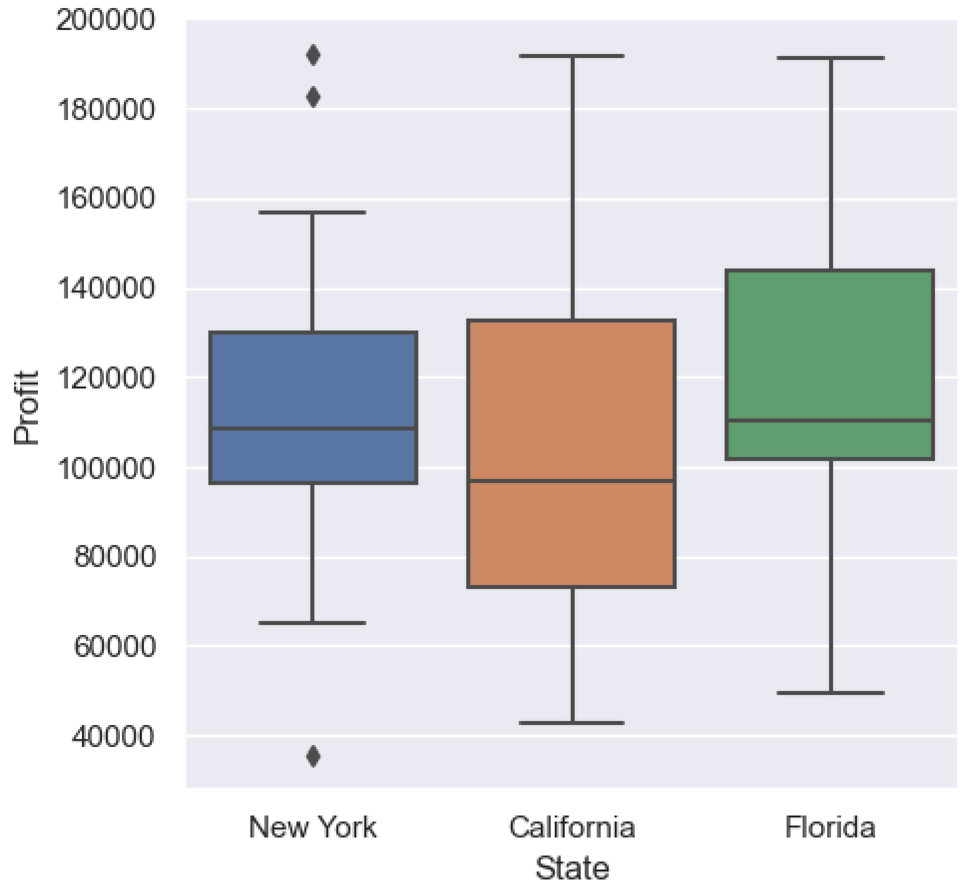
```
outliers = ['Profit']
plt.rcParams['figure.figsize'] = [5,5]
sns.boxplot(data=df[outliers], orient="v", palette="Set2" , width=0.7)
plt.title("Outliers Variable Distribution")
plt.ylabel("Profit Range")
plt.xlabel("Continuous Variable")

plt.show()
```



In [32]:

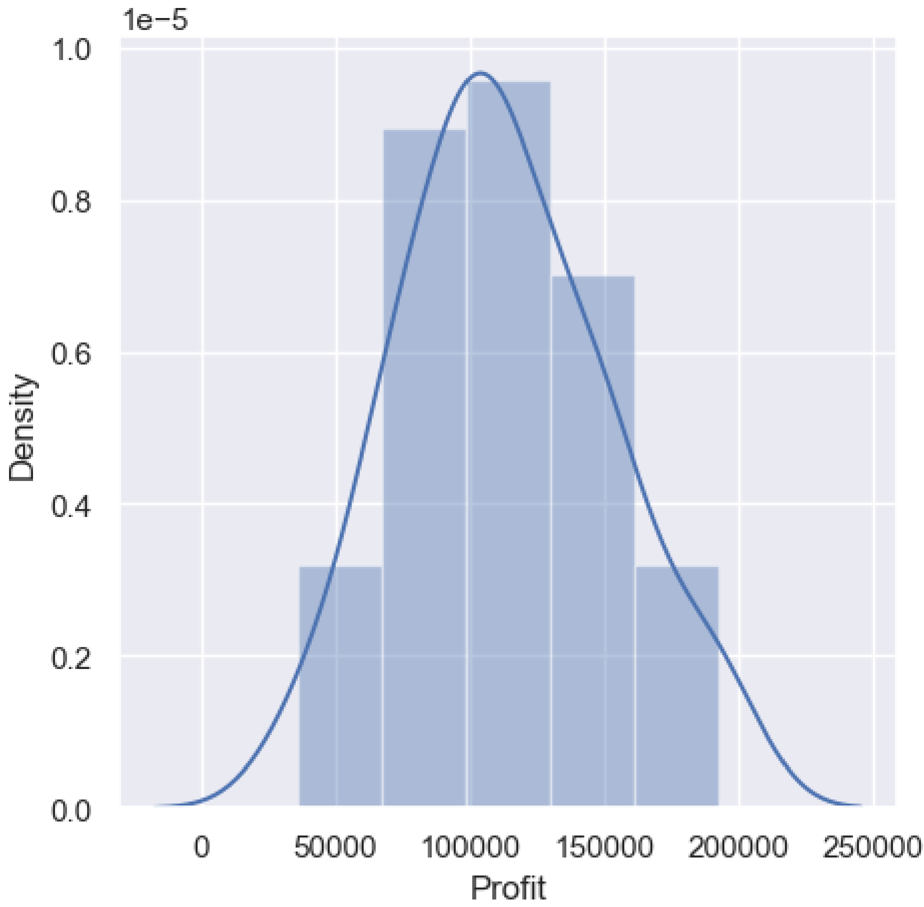
```
sns.boxplot(x = 'State', y = 'Profit', data = df)
plt.show()
```



Now we have the whole picture. The outlier was from the New York column, and one needs to treat it.

In [33]:

```
sns.distplot(df['Profit'],bins=5,kde=True)
plt.show()
```



Section Summary

We have Gaussian Distribution(a bell-shaped curve) here, which is excellent. The dataset is symmetric around the mean and has the same mean, median, and mode.

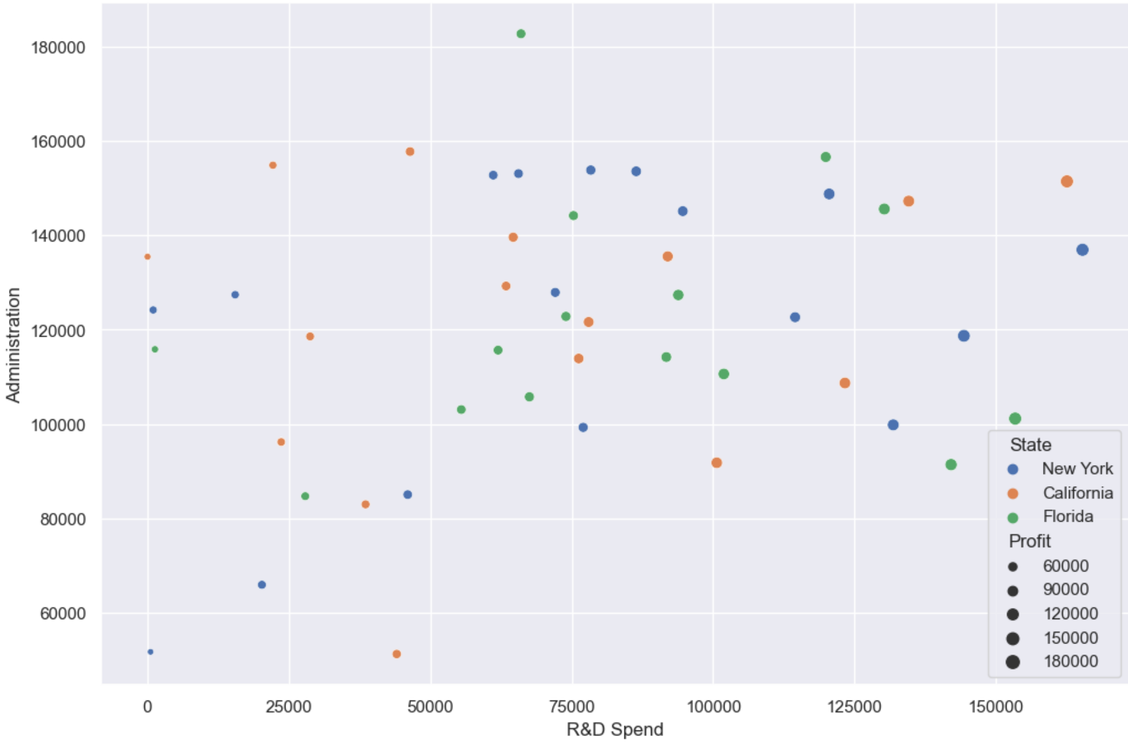
According to data, we can say our data has good distribution, no null and duplicate values. Also, there are a few outliers that need to be treated. All the neumerical data are present in float.

In [34]:

```
plt.figure(figsize=(12,8))
sns.scatterplot(data=df,x="R&D Spend",y="Administration",hue="State", size="Profit")
```

Out[34]:

```
<AxesSubplot:xlabel='R&D Spend', ylabel='Administration'>
```

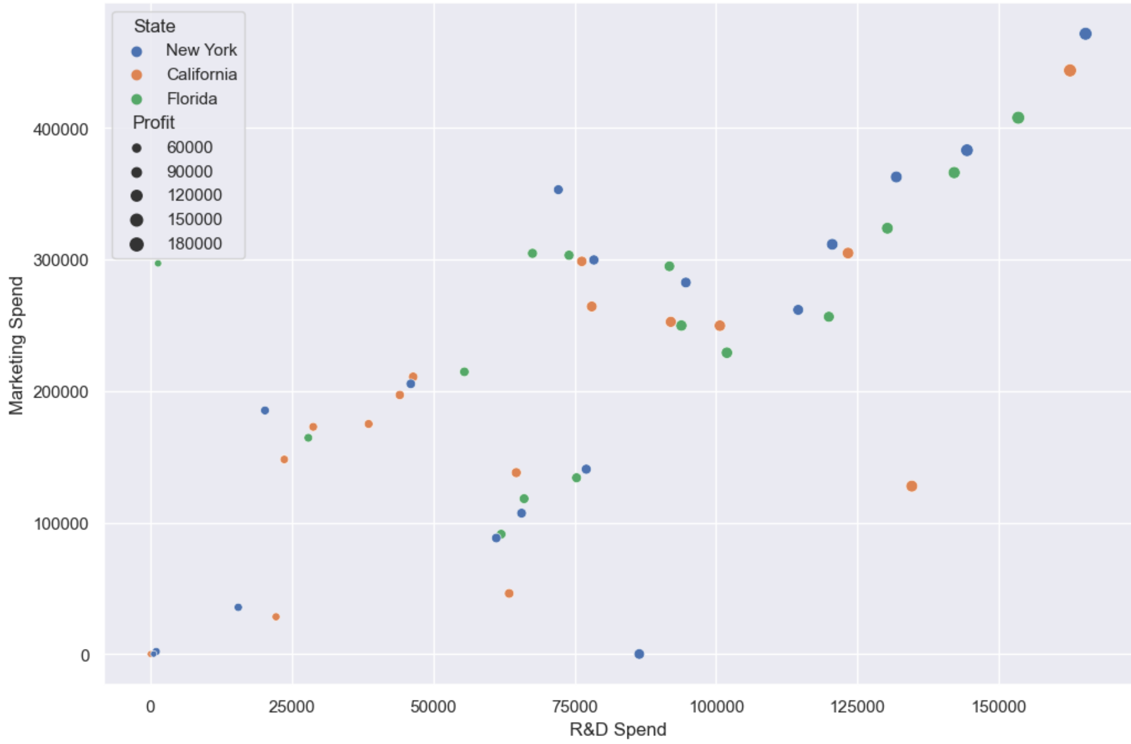


In [35]:

```
plt.figure(figsize=(12,8))
sns.scatterplot(data=df,x="R&D Spend",y="Marketing Spend",hue="State", size="Profit"
```

Out[35]:

<AxesSubplot:xlabel='R&D Spend', ylabel='Marketing Spend'>

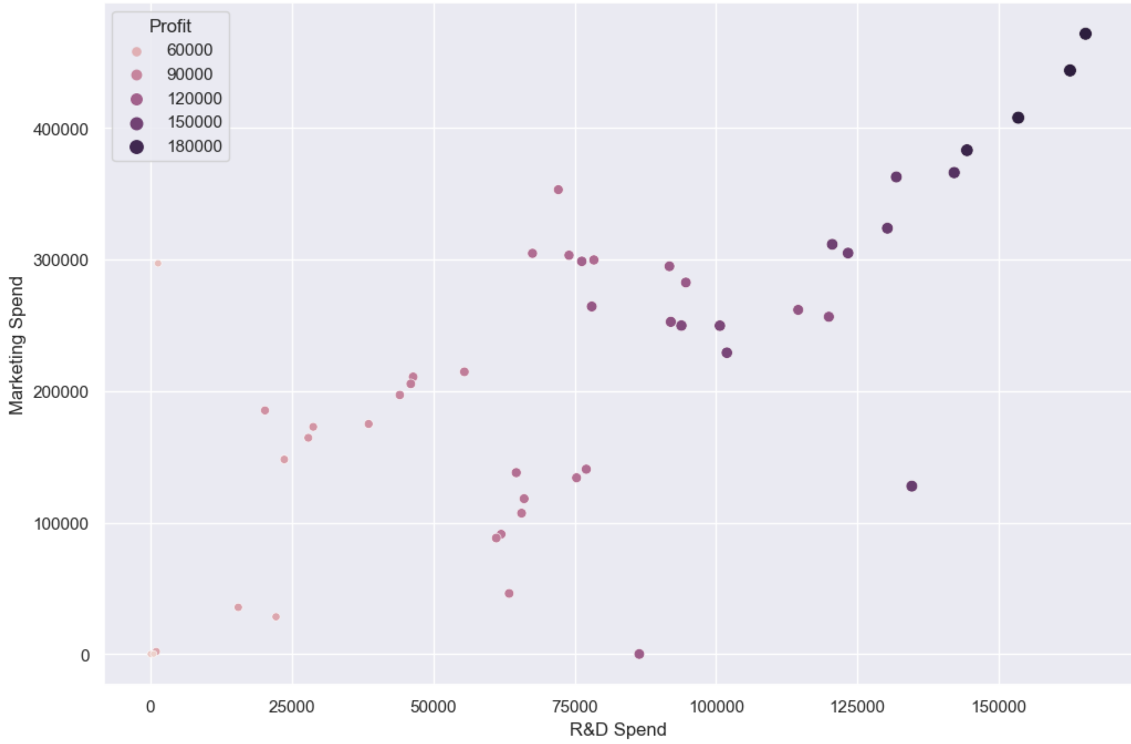


In [36]:

```
plt.figure(figsize=(12,8))
sns.scatterplot(data=df,x="R&D Spend",y="Marketing Spend",hue="Profit", size="Profit
```

Out[36]:

```
<AxesSubplot:xlabel='R&D Spend', ylabel='Marketing Spend'>
```

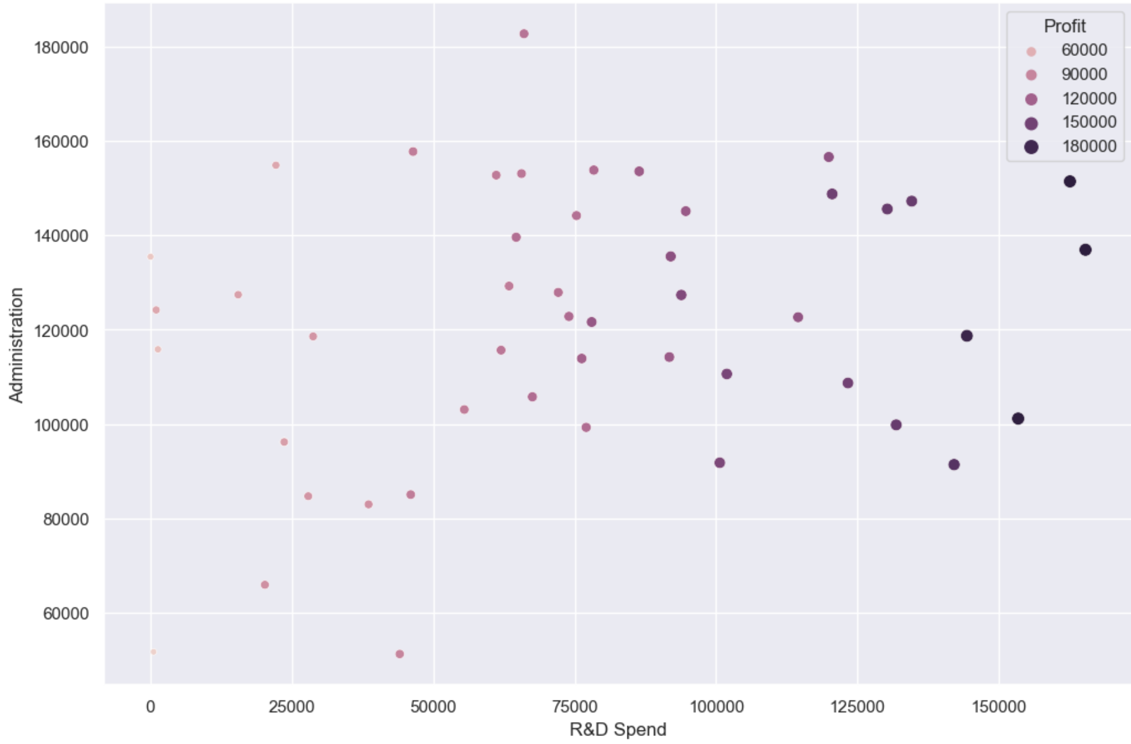


In [37]:

```
plt.figure(figsize=(12,8))
sns.scatterplot(data=df,x="R&D Spend",y="Administration",hue="Profit", size="Profit"
```

Out[37]:

```
<AxesSubplot:xlabel='R&D Spend', ylabel='Administration'>
```

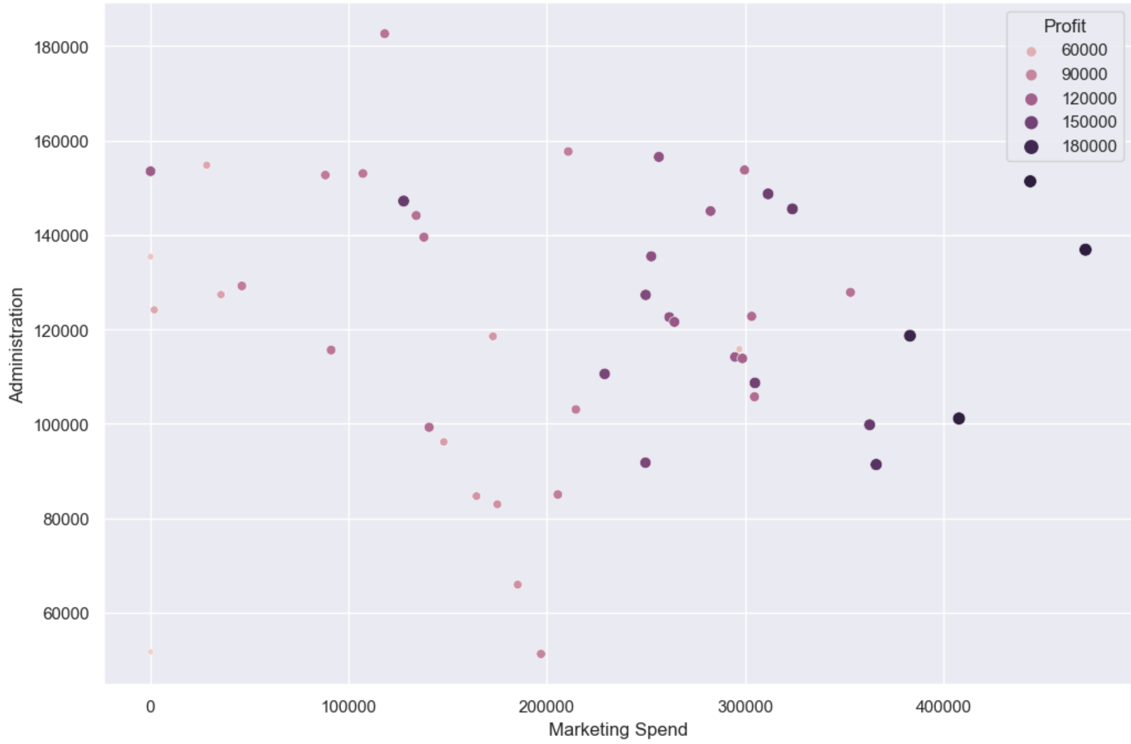


In [38]:

```
plt.figure(figsize=(12,8))
sns.scatterplot(data=df,x="Marketing Spend",y="Administration",hue="Profit", size="P
```

Out[38]:

```
<AxesSubplot:xlabel='Marketing Spend', ylabel='Administration'>
```

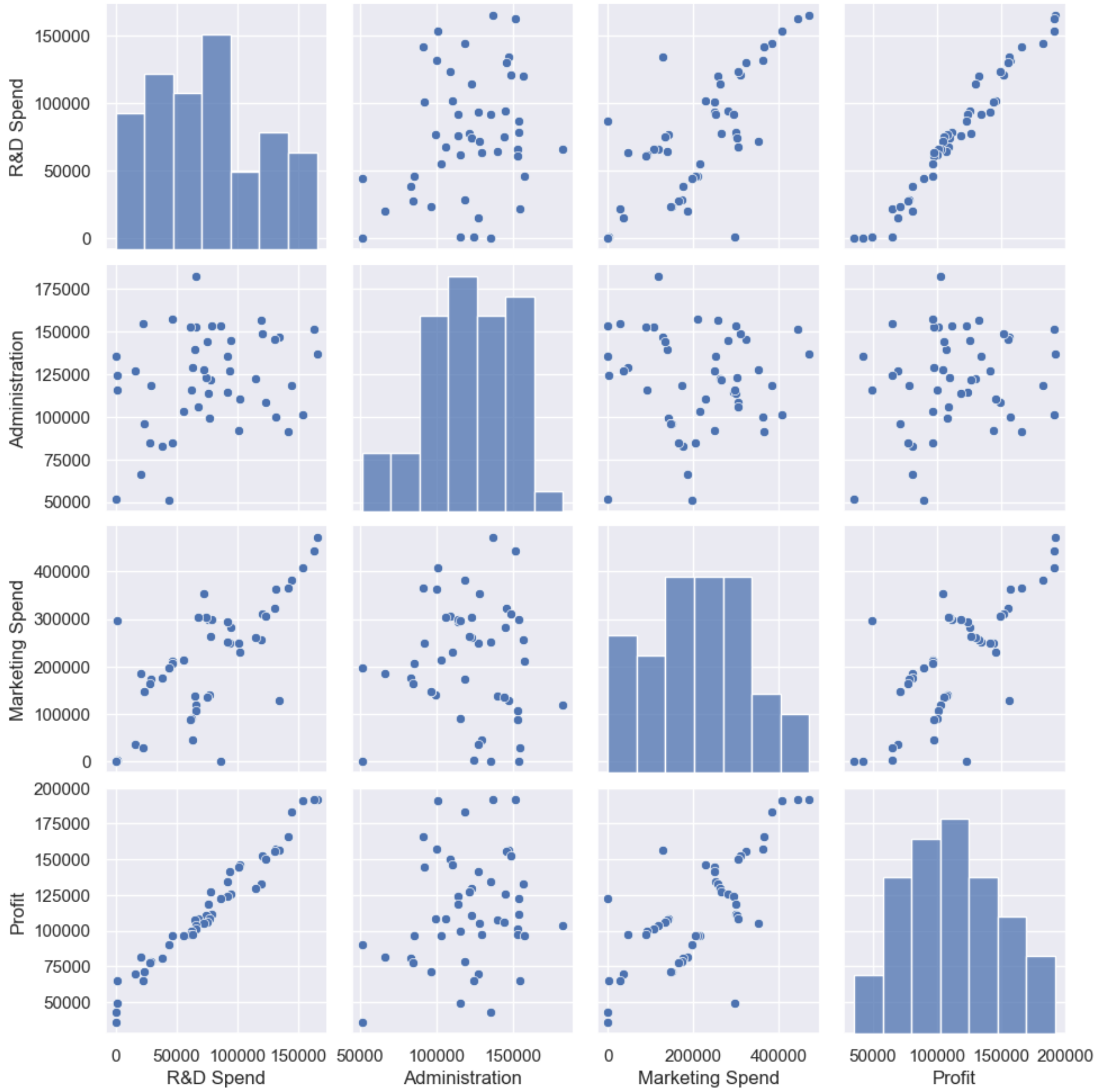


In [39]:

```
sns.pairplot(df)
```

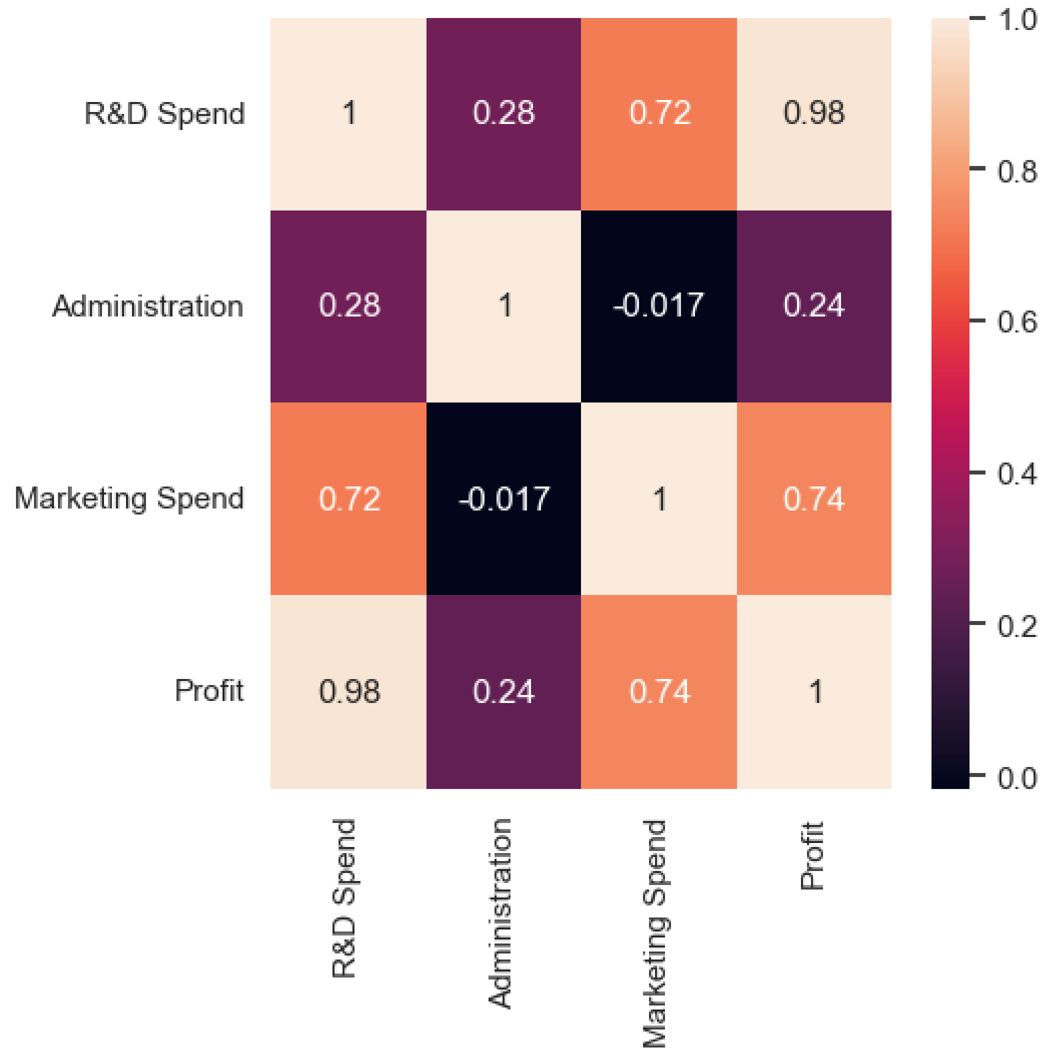
Out[39]:

<seaborn.axisgrid.PairGrid at 0x1d64d45ddc0>



In [40]:

```
sns.heatmap(df.corr(), annot=True)
plt.show()
```



As this task is based on the problem of regression so I will be using the Linear regression algorithm to train the profit prediction model. So let's prepare the data so that we can fit it into the model:

In [41]:

```
features_df= df[["R&D Spend", "Administration", "Marketing Spend"]]
target_df= df["Profit"]
```

In [42]:

```
from sklearn.model_selection import train_test_split

features_train, features_val, target_train, target_val = train_test_split(features_c
```

Linear Regression

In [43]:

```
LR_model = LinearRegression()
LR_model.fit(features_train, target_train)
predictions = LR_model.predict(features_train)
predictions_val = LR_model.predict(features_val)
compare = pd.DataFrame({'Actuals' : target_train, 'predictions': predictions, 'diffr
compare_val = pd.DataFrame({'Actuals': target_val, 'predictions': predictions_val, '
print(compare_val)
```

```
        Actuals    predictions    diffrence
6     156122.51  159029.580688  2907.070688
36     71498.49   71534.197065    35.707065
37     89949.14   91216.348988  1267.208988
28    103282.38  101446.356159  1836.023841
43     69758.98   61176.605519  8582.374481
49     71498.49   71534.701654    36.211654
5     156991.12  163808.164575  6817.044575
33     96778.92   98493.883958  1714.963958
20    118474.03  116608.096799  1865.933201
42     71498.49   71536.140137    37.650137
```

In [44]:

```
from sklearn.metrics import mean_absolute_error
mae = mean_absolute_error(target_val, predictions_val)
print("Mean Absolute Error is :" ,mae)
from sklearn.metrics import mean_squared_error
mse = mean_squared_error(target_val, predictions_val)
print("Mean Squarred Error is :" ,mse*100)
rmse = np.sqrt(mean_squared_error(target_val, predictions_val))
print("Root Mean Squarred Error is : ",rmse*100)
from sklearn.metrics import r2_score
r2Score = r2_score(target_val, predictions_val)
print("R2 score of model is :" ,r2Score*100)
```

```
Mean Absolute Error is : 2510.0188587667253
Mean Squarred Error is : 1399839225.107273
Root Mean Squarred Error is :  374144.2536117952
R2 score of model is : 98.62885676083069
```

Decision Tree Regressor

In [45]:

```
from sklearn.tree import DecisionTreeRegressor
clr = DecisionTreeRegressor()
clr.fit(features_train, target_train)
predictions = clr.predict(features_train)
predictions_val = clr.predict(features_val)
compare = pd.DataFrame({'Actuals' : target_train, 'predictions': predictions, 'diffr
compare_val = pd.DataFrame({'Actuals': target_val, 'predictions': predictions_val, '
print(compare_val)
```

```
      Actuals  predictions  diffrence
6   156122.51    141585.52   14536.99
36   71498.49     77798.83    6300.34
37   89949.14     96479.51    6530.37
28  103282.38    101004.64    2277.74
43   69758.98     77798.83    8039.85
49   71498.49     77798.83    6300.34
5   156991.12    166187.94    9196.82
33   96778.92     97483.56     704.64
20  118474.03    108552.04    9921.99
42   71498.49     77798.83    6300.34
```

In [46]:

```
from sklearn.metrics import mean_absolute_error
mae = mean_absolute_error(target_val, predictions_val)
print("Mean Absolute Error is :" ,mae)
from sklearn.metrics import mean_squared_error
mse = mean_squared_error(target_val, predictions_val)
print("Mean Squarred Error is :" ,mse*100)
rmse = np.sqrt(mean_squared_error(target_val, predictions_val))
print("Root Mean Squarred Error is : ",rmse*100)
from sklearn.metrics import r2_score
r2Score = r2_score(target_val, predictions_val)
print("R2 score of model is :" ,r2Score*100)
```

```
Mean Absolute Error is : 7010.942000000003
Mean Squarred Error is : 6264038516.760007
Root Mean Squarred Error is :  791456.7907826685
R2 score of model is : 93.86437105911683
```

Gradient Boosting Regressor

In [47]:

```
from sklearn.ensemble import GradientBoostingRegressor, AdaBoostRegressor
gbr = GradientBoostingRegressor()
gbr.fit(features_train, target_train)
predictions = gbr.predict(features_train)
predictions_val = gbr.predict(features_val)
compare = pd.DataFrame({'Actuals' : target_train, 'predictions': predictions, 'diffr
compare_val = pd.DataFrame({'Actuals': target_val, 'predictions': predictions_val, '
print(compare_val)
```

```
     Actuals    predictions    diffrence
6   156122.51  147440.675457  8681.834543
36   71498.49   75162.886234  3664.396234
37   89949.14   99371.023384  9421.883384
28  103282.38  101595.431269  1686.948731
43   69758.98   71310.106461  1551.126461
49   71498.49   75162.886234  3664.396234
5   156991.12  160920.113514  3928.993514
33   96778.92   99586.329547  2807.409547
20  118474.03  108956.472470  9517.557530
42   71498.49   75162.886234  3664.396234
```

In [48]:

```
from sklearn.metrics import mean_absolute_error
mae = mean_absolute_error(target_val, predictions_val)
print("Mean Absolute Error is :" ,mae)
from sklearn.metrics import mean_squared_error
mse = mean_squared_error(target_val, predictions_val)
print("Mean Squarred Error is :" ,mse*100)
rmse = np.sqrt(mean_squared_error(target_val, predictions_val))
print("Root Mean Squarred Error is : ",rmse*100)
from sklearn.metrics import r2_score
r2Score = r2_score(target_val, predictions_val)
print("R2 score of model is :" ,r2Score*100)
```

```
Mean Absolute Error is : 4858.894241434304
Mean Squarred Error is : 3235837658.902952
Root Mean Squarred Error is :  568844.2369316008
R2 score of model is : 96.83049535298296
```

Adda Boost Regressor

In [49]:

```
from sklearn.ensemble import GradientBoostingRegressor, AdaBoostRegressor
abr = AdaBoostRegressor()
abr.fit(features_train, target_train)
predictions = abr.predict(features_train)
predictions_val = abr.predict(features_val)
compare = pd.DataFrame({'Actuals' : target_train, 'predictions': predictions, 'diffr
compare_val = pd.DataFrame({'Actuals': target_val, 'predictions': predictions_val, '
print(compare_val)
```

```
      Actuals    predictions     diffrence
6   156122.51  150867.150000   5255.360000
36   71498.49   78022.196667   6523.706667
37   89949.14   96712.800000   6763.660000
28  103282.38  104207.576000    925.196000
43   69758.98   67282.176667   2476.803333
49   71498.49   78022.196667   6523.706667
5   156991.12  159218.570000   2227.450000
33   96778.92   98400.333333   1621.413333
20  118474.03  108348.382000  10125.648000
42   71498.49   78022.196667   6523.706667
```

In [50]:

```
from sklearn.metrics import mean_absolute_error
mae = mean_absolute_error(target_val, predictions_val)
print("Mean Absolute Error is :" ,mae)
from sklearn.metrics import mean_squared_error
mse = mean_squared_error(target_val, predictions_val)
print("Mean Squarred Error is :" ,mse*100)
rmse = np.sqrt(mean_squared_error(target_val, predictions_val))
print("Root Mean Squarred Error is : ",rmse*100)
from sklearn.metrics import r2_score
r2Score = r2_score(target_val, predictions_val)
print("R2 score of model is :" ,r2Score*100)
```

```
Mean Absolute Error is : 4896.665066666673
Mean Squarred Error is : 3181519558.536763
Root Mean Squarred Error is :  564049.6040719082
R2 score of model is : 96.88369996015913
```

In [51]:

```
LR_model = LinearRegression()
LR_model.fit(features_train, target_train)
predictions = LR_model.predict(features_train)
predictions_val = LR_model.predict(features_val)
compare = pd.DataFrame({'Actuals' : target_train, 'predictions': predictions, 'diffr
compare_val = pd.DataFrame({'Actuals': target_val, 'predictions': predictions_val, '
print(compare_val)
```

```
      Actuals    predictions    diffrence
6   156122.51  159029.580688  2907.070688
36   71498.49   71534.197065    35.707065
37   89949.14   91216.348988  1267.208988
28  103282.38  101446.356159  1836.023841
43   69758.98   61176.605519  8582.374481
49   71498.49   71534.701654    36.211654
5   156991.12  163808.164575  6817.044575
33   96778.92   98493.883958  1714.963958
20  118474.03  116608.096799  1865.933201
42   71498.49   71536.140137    37.650137
```

Confirming Hypothesis

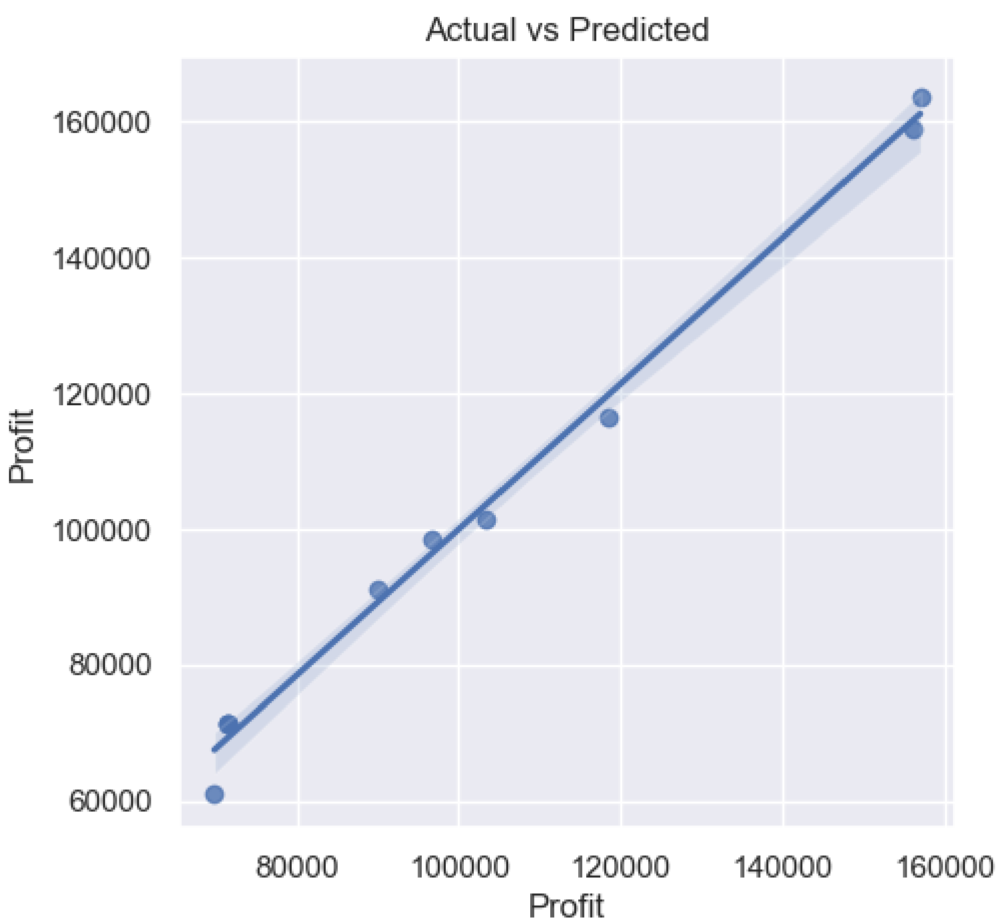
Often the scores are not self-explanatory, so visualization is required. We can visualize to confirm our hypotheses by plotting the actual prediction and the regression line fit using a regression plot.

In [52]:

```python
plt.title('Actual vs Predicted')
plt.xlabel('Total cost')
plt.ylabel('Profit')
sns.regplot(x=target_val, y=predictions_val, data=df)
```

Out[52]:

```
<AxesSubplot:title={'center':'Actual vs Predicted'}, xlabel='Profit', ylab
el='Profit'>
```



Since the data set is small, the best mechine learing model is linear regression. So we can select this model as our final model.

We can collect more data and we can apply complex algorithem to it to make the model as the best model.

Model Deployment Now that we have our final model up and running, the user will be required a way to use it. One of the best ways to do it is to deploy the model in the cloud as a web app, which includes two parts, writing the backend and adding UI elements.

So to make our life simpler, we will be using streamlit, a go-to library for both backend and frontend development due to its extensive support for python and HTML embedded widgets.

So let's get started.

1. Creating The Frontend To create one, the library offers the embedded HTML and widgets support for leveraging to make the button, fields, image anchors, titles, and more.
2. Writing The Backend Here the backend refers to calling model architecture and handling the entire preprocessing laber_encoding step. We will take here to load the model and validate the inputs. This

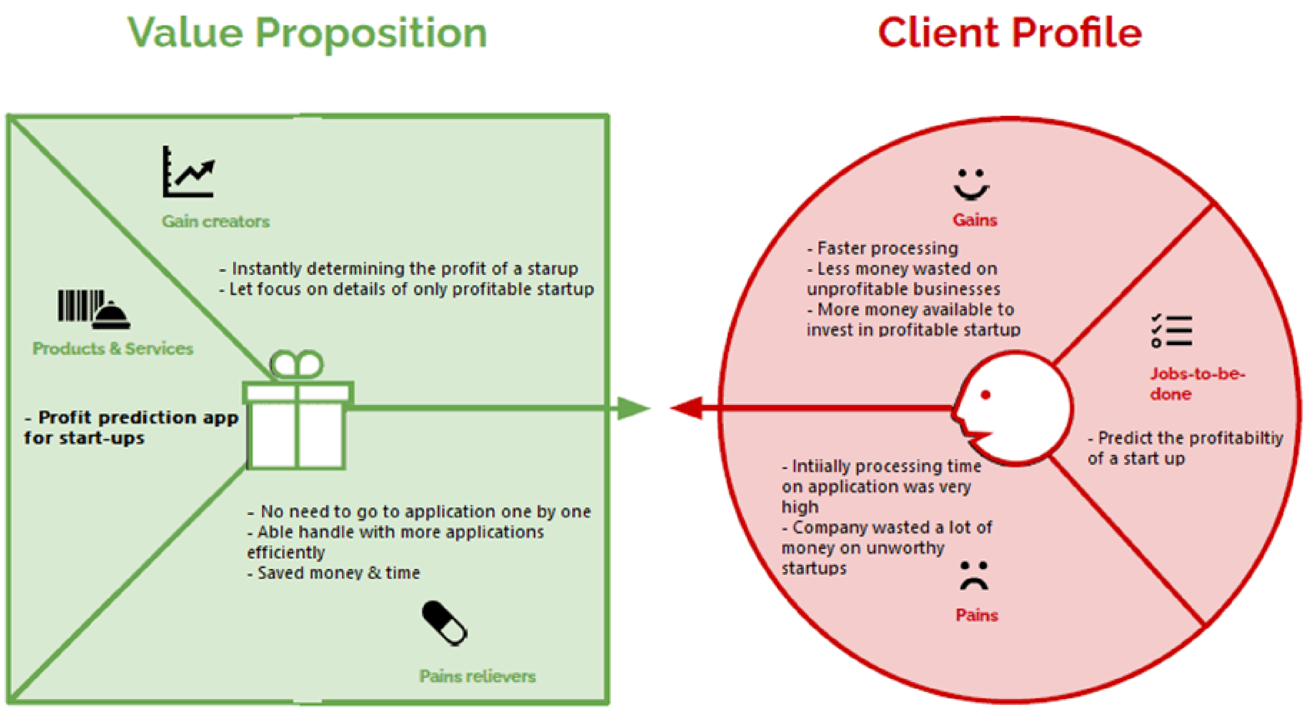
way, we can have more granular control over versioning the model
3. Hosting On Cloud- Additional Requirements Streamlit also allows hosting ML apps to the cloud for free. Of course, you need to signup. However, it requires some other processes

17. Business Model :

To make a successful business model, many components must be critically evaluated. There have been many arguments that what a business model should include, but considering the market and the competition, we must consider 10 points which are discussed in detail.

1. Value Proposition:

Any business starts by defining value proposition, which describes the unique value your business offers to customers. What problem does your product or service solve? What needs or desires does it fulfil? Clearly articulate the benefits and advantages that set your business apart from competitors. So, in our case we can clearly see that when a start-up is in early stage and it needs funding from the angel-investors, venture capitalists and other investors etc., there goes a lot of time scanning all the companies' documents, profit they are making etc. So, what we are doing is making the process easy for them by offering them a second hand and helping in automating the process. Now based on data our model can predict that which start-ups are going to be successful, or which are not. So, they can pay deep attention to only those start-ups which are going to make money in the future. And we all know that, out of 30 funded start-ups, only one get successful. So, the investors can save money as well as time. There could be second customers as well, which are start-up themselves. Through our model, they can predict that whether they are going to be successful or not. And if model is predicting outcome as "No", they can change approaches to their way of doing business to see the different result. So, time and time they can check the expected outcome of their effort. The model can also help with improving the accuracy of the profit predictions, identifying opportunities for growth, optimizing pricing strategies, or reducing costs.

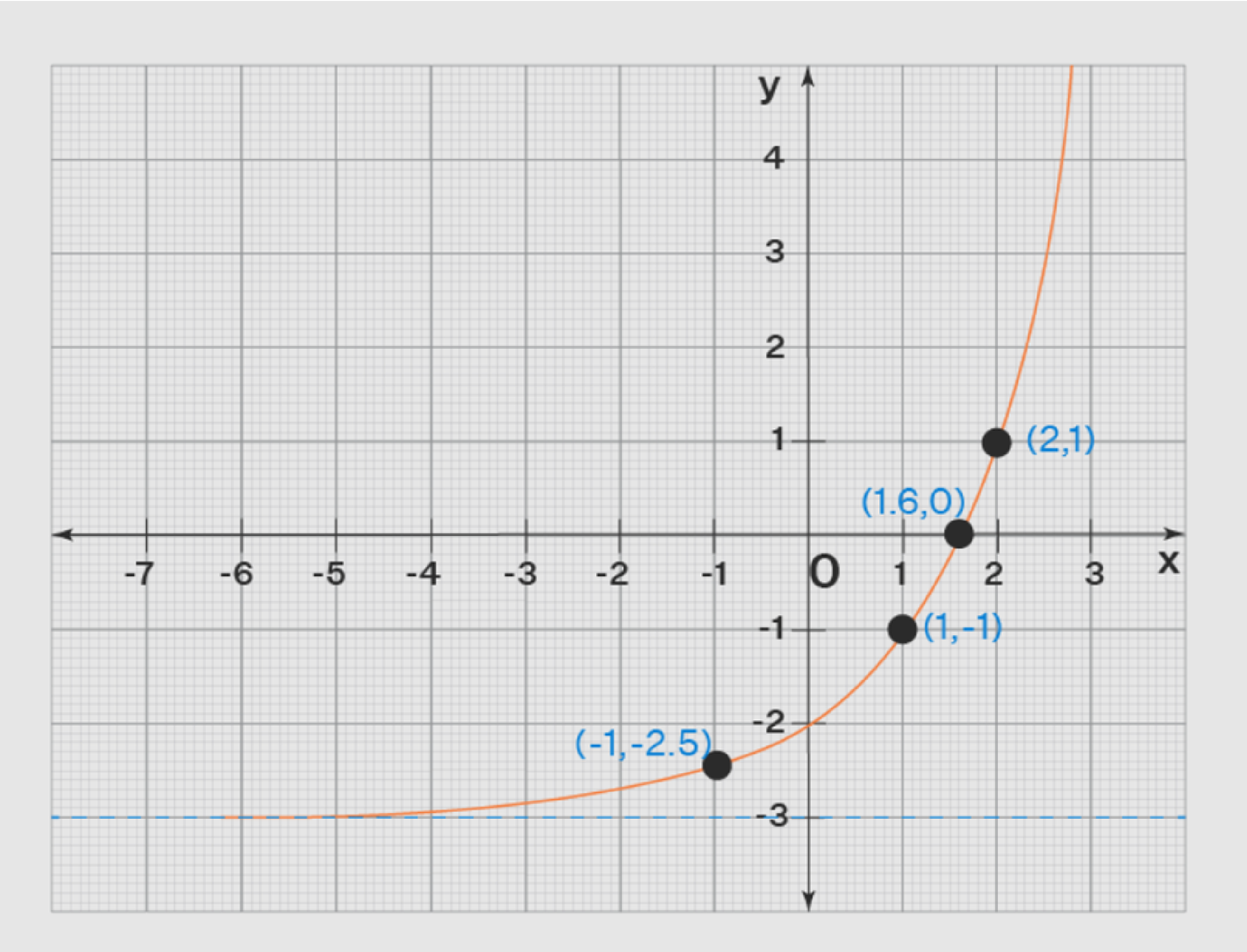


2. Target Market:

Identifying the target market segment is a key part of developing a business model. As we have discussed above our product is mainly going to cater people or organizations who have to deal with the investment decisions for startups. A venture-company and angel investors receive a lot of the application from start-up founders, which makes it burdensome for these companies to go through all the details and decide on which to fund. Now with the future profit prediction they can know, how much a start-up is going to make on future. So, they can now focus on details of profit-making companies and discard others.

3. Revenue Streams:

This step will define how our business will generate revenue. Identifying the primary sources of income, such as product sales, subscriptions, licensing fees, or advertising are main tasks here. Consider different pricing strategies and revenue models that align with your value proposition and target market. There would be many ways to generate the revenue from this model. As it will save a lot of money and time for the venture capital organization. The two feasible ways are:
a) Subscription model – Businesses can offer access to their profit prediction machine learning model on a subscription basis. Customer would only pay a recurring fee to use the model to predict the futures.
b)Pay per-use model- Similar to a subscription model, businesses can charge customers on a pay-per-use basis. Customer would only pay for the predictions they need, rather than a recurring subscription fee.



4. Cost Structure:

Next step is to determine the cost structure associated with operating business. Two types of costs need to be considered. Fixed costs and variable costs.

Fixed Costs (One time or Infrequent costs):

1. Development Costs: This includes the initial investment in building the machine learning model, such as hiring data scientists, machine learning experts, and software developers to create the algorithm and infrastructure. This can range from INR 10,00,000 to 25,00,000 or more, depending on the complexity and expertise required for developing the machine learning model.
2. Technology Infrastructure: Setting up the necessary hardware and software infrastructure to support the model, including servers, cloud computing services, data storage, and maintenance costs. The costs for setting up servers, cloud computing services, and storage can range from INR 2,00,000 to 5,00,000 or higher, depending on our requirements.
3. Research and Data Acquisition: Acquiring relevant datasets and conducting research to enhance the accuracy and effectiveness of the model can incur fixed costs. Allocating INR 1,00,000 to 5,00,000 or more for research and data acquisition efforts is a rough estimate, considering the need to acquire relevant datasets or conduct additional research.
4. Regulatory Compliance: If there are regulatory requirements or certifications needed to operate in the industry or handle sensitive data, there might be fixed costs associated with compliance measures. Costs associated with regulatory compliance can vary depending on the specific requirements. Budgeting around INR 1,00,000 to 3,00,000 or more for compliance measures is a general estimate.

Variable Costs(Ongoing or Usage-based Costs):

1. Data Processing and Analysis: As part of the subscription service, there may be variable costs related to data processing and analysis, such as computational expenses for running predictions on large datasets or using cloud-based machine learning services. This can range from INR 10,00,000 to 25,00,000 or more, depending on the complexity and expertise required for developing the machine learning model.
2. Support and Maintenance: Providing customer support, troubleshooting, and maintaining the model's performance can lead to variable costs. This includes costs associated with addressing customer inquiries, resolving technical issues, and ensuring the model is up to date. Allocating resources for customer support and maintenance can range from INR 25,000 to 1,00,000 or more per month, depending on the level of support and the size of the subscriber base.
3. Scaling and Infrastructure Costs: If our subscriber base grows, we may need to invest in scaling up our infrastructure, including additional server capacity, computing resources, or upgrading software tools. These costs can vary depending on the number of subscribers and usage patterns. Budgeting around INR 50,000 to 2,00,000 or more per month for scaling infrastructure is a general estimate.
4. Marketing and Sales: Variable costs associated with marketing and sales efforts to acquire new subscribers and retain existing ones. This can include advertising, promotions, sales team salaries or commissions, and other marketing-related expenses. The costs associated with marketing and sales efforts can vary significantly depending on the strategies employed. Budgeting around INR 1,00,000 to 5,00,000 or more per month for marketing and sales activities is a rough estimate. Note: These are just the estimates depending on the current market situation.

5. Key Activities:

For a machine learning model focused on start-up profit prediction, the key activities would involve developing and deploying the model, as well as ongoing maintenance and improvement. Here are some key activities to consider:

1. Data Collection and Preparation: Collect relevant data from various sources such as financial statements, sales records, market data, and industry benchmarks. Clean and preprocess the data, handle missing values, perform feature engineering, and prepare it for training the machine learning model.
2. Model Development: Develop and train the machine learning model using suitable algorithms and techniques for profit prediction. This involves selecting the appropriate features, splitting the data into training and testing sets, and tuning the model parameters for optimal performance.
3. Model Evaluation and Validation: Assess the performance of the model using appropriate evaluation metrics such as accuracy, precision, recall, or mean squared error. Validate the model's predictions against known profit values or ground truth data. Iterate and refine the model if necessary.
4. Integration and Deployment: Integrate the trained model into a production environment or software system. Develop APIs or interfaces to enable seamless integration with other applications or platforms. Ensure the model is deployed in a scalable and efficient manner to handle real-time prediction requests.
5. Monitoring and Maintenance: Continuously monitor the model's performance and behaviour in the production environment. Set up monitoring systems to detect anomalies, data drift, or degradation in model performance. Regularly update and retrain the model with fresh data to maintain accuracy and relevance.
6. Interpretation and Explanation: Understand and interpret the model's predictions and provide explanations to stakeholders. Identify the key factors or features that contribute most to profit prediction. Communicate the model's insights effectively to decision-makers.
7. Continuous Improvement: Seek feedback from users, gather additional data, and refine the model over time. Incorporate new features, explore advanced algorithms, or leverage techniques such as ensemble learning or model stacking to improve prediction accuracy and robustness.
8. Ethical Considerations: Address ethical considerations related to privacy, bias, and fairness in the data and model. Ensure the model's predictions and recommendations align with ethical standards and legal requirements.

6. Key Resources:

Key resources we would need to do the projects includes physical assets like machines, subscription to clouds etc. We also need human resources like data scientist, machine learning engineers, market analyst etc. We also need to be financially capable to fund the cost of the project.

7. Channels:

Next step is to define the channels trough which we reach and interact with the customers. We can use direct email to communicate with the intended organization or in some cases we can also make use of B2B sales. But this is not necessary as the product is not so complex, even a digital product tour or product demo can explain that. So, we would prefer online channels here.

8. Customer Relationships:

Customer Relationships could be ensured in several ways. First, we have to consider that we are using machine learning model, not every customer should be able to understand how it works in technical terms, so we need to speak to customers in very plain language that will help them understand its advantages and limitations. Keeping the term simple we have to communicate with them that how this model would help them in making profitability. To make a better customer relationship, personalization could also be offer to them like if a company deals with mostly certain industry of customers, then a variable which is used in that industry could also be added to make prediction, obviously if that does a good job. One other important aspect of customer relationship is customer support. This becomes particularly useful in digital products. Multiple channels would be provided like email, phone, and live chat. Another important aspect is to educate our customers on how to make the most of profit prediction model. We will provide documentation, tutorials, and resources that explain how to interpret the model's predictions, integrate it into their workflows, and

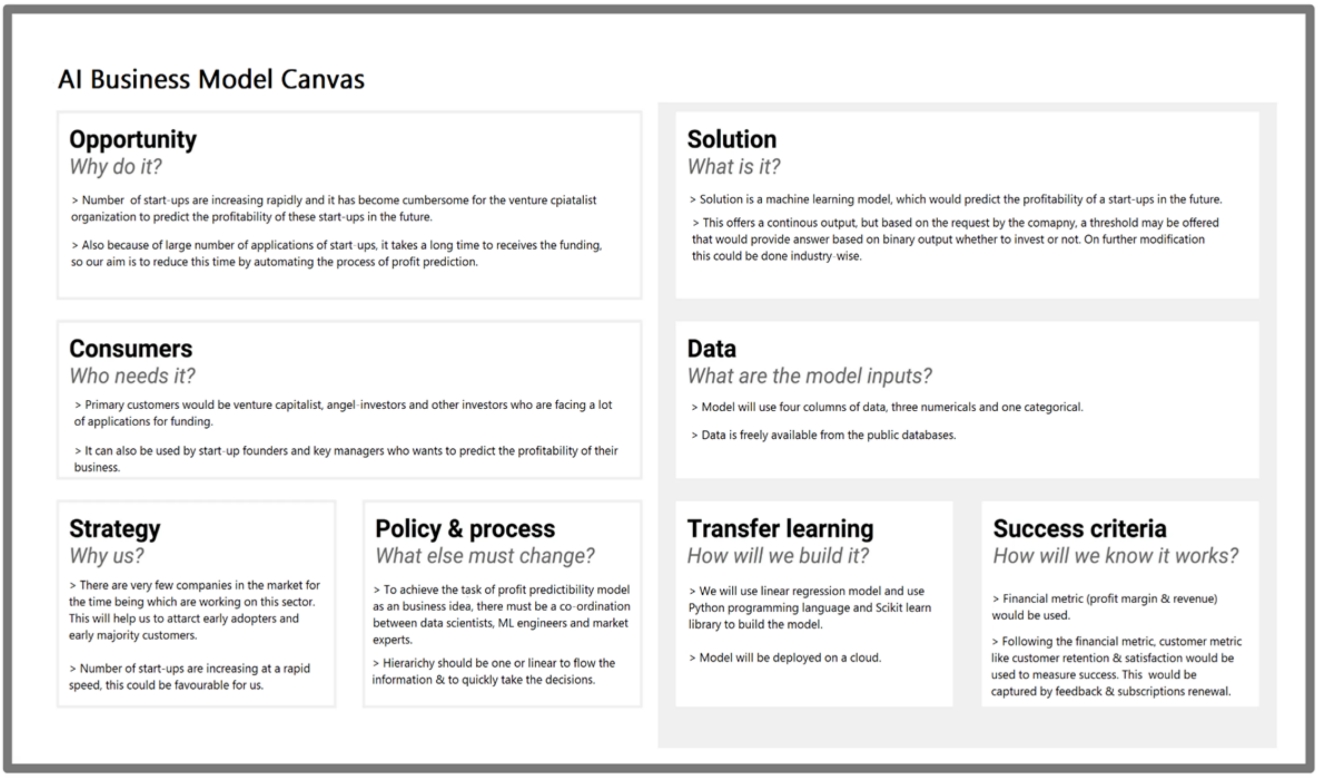
Table: Customer Relationship Factors Explained

Factor	Explanation
Use plain language	Avoid jargons and explain the function of ML model in simple terms to have a better communication
Offer personalization	For catering a special type of industry, a new commonly used variable of that industry could be added into model to make it more reliable
Customer Support	Focus on omni-channel presence. Multiple channels would be provided like email, phone, and live chat, all integrated.
Providing product demos, guide etc	Provide documentation, tutorials, and resources that explain how to interpret the model's predictions, integrate it into their workflows, and leverage its insights effectively.
Feedback consideration	Taking their feedback in consideration, so we can deliver according to their expectation, helping in building long-term relationship.

9. Key Metrics:

Key performance indicators for our product would be a financial metric of profit margin. After focusing on financial metric, we will also measure our success by considering the customer metrics. Through the feedback system we can measure the customer satisfaction and as we are going to follow the subscription-based approach, we can measure the retention rate by the number of people who have renewed the contract with our company. If there would be more renewal, we can be sure that our model is doing a good job.

The summary of the above discussion is shown in an AI business model canvas below. This contains data like opportunities, solution, consumers etc.



19. Financial Equation:

The provided statement introduces a financial equation to determine the profit of a project based on the growth of the customer base. Let's break it down into its components:

The equation is: Proft = (PricSub * GR ^ T * N) - (MLEng + WebDev+ InfrSt+ DataAqu)

In this equation:

Profit represents the profit generated by the model over time. PricSub is Price of the subscription (subscription fee charged to users), GR is Growth rate, T = Time interval (in months or years), N is Number of subscribers, (MLEng + WebDev+ InfrSt+ DataAqu) represents the cost incurred in developing the machine learning model. It takes into account the salaries of ML engineer(MLEng), one full-stack web developer (WebDev), Infrastructure costs including Office rent, equipment costs etc (InfrSt) and data acquisition cost (DataAqu).

The graph illustrates the relationship between time (T) and profit in a generalized manner, considering factors such as the growth rate (GR), subscription price (PricSub), and number of subscribers (N). It demonstrates how profit changes over time, showcasing an exponential increase due to the compounding effect of these factors.

It's important to note that the graph is a representation and does not specify actual values for the growth rate, time interval, subscription price, or number of subscribers. These values would need to be determined based on the specific context of the application.

Furthermore, to develop a comprehensive financial model for the app, other factors must be taken into account. These may include the churn rate (the rate at which subscribers stop using the app), customer acquisition costs (the expenses associated with acquiring new subscribers), and lifetime value analysis (the projected value a subscriber brings over their entire customer lifespan).

Considering these additional factors alongside the graph's representation would lead to a more accurate and comprehensive financial model for the app.

18. Conclusion :

In conclusion, our project successfully developed and tested a machine learning model for profit prediction. Through our analysis of historical data, we identified key factors that are predictive of profit, and used these factors to train a machine learning model using various regression algorithms. We evaluated the performance of our model using cross-validation techniques and found that it outperformed traditional statistical models.

Our findings suggest that machine learning techniques can be effectively used for profit prediction, providing businesses with valuable insights for decision-making. By accurately predicting profit, businesses can make informed decisions about resource allocation, pricing strategies, and investment opportunities, among other factors, leading to better financial performance and overall success.

Our project has some limitations, such as the reliance on historical data and assumptions about the relationships between variables. Future research could explore the use of real-time data and alternative algorithms to improve the accuracy of profit prediction models.

Overall, our project demonstrates the potential of machine learning for profit prediction and highlights the importance of data-driven decision-making in business. We hope that our findings and methodology can be useful for businesses seeking to improve their financial performance through predictive analytics.

19. References :

Reference books

1. "Hands-On Machine Learning for Algorithmic Trading: Design and implement investment strategies based on smart algorithms that learn from data using Python" by Stefan Jansen - This book covers how to use machine learning techniques for algorithmic trading, including profit prediction models.
2. "Python Machine Learning: Machine Learning and Deep Learning with Python, scikit-learn, and TensorFlow" by Sebastian Raschka and Vahid Mirjalili - This book covers the basics of machine learning and deep learning using Python, and includes a chapter on regression analysis, which is a common technique for profit prediction.
3. "Data Science for Business: What You Need to Know about Data Mining and Data-Analytic Thinking" by Foster Provost and Tom Fawcett - This book provides an overview of data science techniques and how they can be applied to business problems, including profit prediction.
4. "Financial Analytics with R: Building a Laptop Laboratory for Data Science" by Mark J. Bennett and Dirk L. Hugen - This book covers how to use R for financial analysis, including building predictive models for financial data such as profit prediction.
5. "Practical Machine Learning for Computer Vision" by Martin Görner, Ryan Gillard, and Valliappa Lakshmanan - While this book is focused on computer vision, it includes a chapter on regression analysis, which can be useful for building profit prediction models.

These books can provide a good foundation for understanding the concepts and techniques used in profit prediction with machine learning, and can help you build your own models for your specific business or industry.

Reference links

https://medium.com/@ShortHills_Tech (https://medium.com/@ShortHills_Tech),

https://www.kaggle.com/code/vikramjeetsinghs (https://www.kaggle.com/code/vikramjeetsinghs),

https://thecleverprogrammer.com/2021/04/29 (https://thecleverprogrammer.com/2021/04/29),

https://rpubs.com/feruzta/LinearRegression (https://rpubs.com/feruzta/LinearRegression)