* **Introduction**
  + Bitcoin is a decentralized cryptocurrency, created in 2009 by an anonymous inventor under the pseudonym Satoshi Nakamoto. I
  + t does not have a central bank behind it that distributes new currency but relies on a network of nodes, i.e., PCs, that manage it in a distributed, peer-to-peer mode; and on the use of strong cryptography to validate and secure transactions.
  + Transactions can be made through the Internet to anyone with a "bitcoin address."
  + Bitcoin's value is determined by the market and the number of people using it.
  + Its blockchain, or public ledger of transactions, is constantly updated and validated by nodes in the network.
  + The cryptocurrency Bitcoin has attracted the attention of many people in recent years.
  + However, it's price fluctuation can be extremely unpredictable, which makes it difficult to predict when the right time to buy or sell this digital currency will be.
  + In this context, prediction Bitcoin prices can be a competitive advantage for investors and traders, as it could allow them to make informed decisions on the right time to enter or exit the market.
  + In this project, I will analyze some machine learning techniques to understand, through the processing of historical data, how accurately the price of Bitcoin can be predicted and whether this can provide added value to cryptocurrency investors and traders.
* **Goal**
  + Is it possible to do price prediction of Bitcoin using machine learning methods in combination with the technical features of its blockchain?
* **Dataset**
  + I chose to collect data on the Bitcoin blockchain using the API of the website Blockchain.org, the most relevant information was retrieved from the last four years to the present day (a period for which there were moments of high volatility but also a lot of price lateralization).
  + The procedure has been made as automatic as possible so that the same periods are considered each time the entire procedure is run.
  + The features taken under consideration were divided into several categories:
    - Currency statistics: describe its price trend (e.g. market price, number of bitcoins in circulation...)
    - Block details: describe the technical characteristics of its blockchain (e.g. block size, number of transactions...)
    - Mining information: describe the characteristics of the consensus mode “Pow” (e.g. miners revenue, difficulty...)
    - Network activity: describe the actual use of Bitcoin as a method of exchange of value (e.g. number of transactions made, cost per transaction...)
* **Project pipeline**
  + The project is structured like this:
    - Data crawling: Bitcoin data retrieval via API call to Blockchain.com
    - Feature engineering: manipulation, visualization and feature extraction
    - Models’ train / validation: to train the models and evaluate them by performing hyperparameter tuning and cross validation
    - Models testing: Test the final models and compare the results to answer the initial question
  + Project carried out with Apache Spark (but during feature engineering I converted the Spark dataframe to a Pandas one to make some plots)
* **Data crawling / Feature engineering**
  + I simply make a call to the api to retrieve the data, check for null values, and save the dataset to disk
  + **Adding new features**
    - I decided to add some features that could help us predict the Bitcoin price:
      * Next market price: represents the price of Bitcoin for the next day (this will be the target variable on which to make predictions)
      * Rate of change: indicator that measures the percentage of price changes over a period of time, allows investors to spot security momentum and other trends
      * Simple Moving Averages: indicators that calculate the average price over a specified number of days. They are commonly used by traders to identify trends and potential buy or sell signals
  + **Dataset spit**
    - I decided to split the dataset into two sets:
      * Train / Validation set: will be used to train the models and validate the performances
      * Test set: will be used to perform price prediction on never-before-seen data (the last 3 months of the original dataset will be used).
  + **Feature selection**
    - All these features will be divided into 3 groups based on their correlation and importance with respect to the market price using the Pearson method and Random Forest Regressor to see the differences according to their use:
      * All: contains all features
      * Most correlated: contains features that have a correlation value > 0.5
      * Least correlated: contains the features that have a correlation value <= 0.5
* **Models train / validation**
  + Several types of regression algorithms will be used, including: Linear Regression, Generalized Linear Regression, Random Forest Regressor and Gradient Boosting Tree Regressor
    - To see their differences and how they perform in the various stages of training / validation and testing.
  + Different types of metrics will be used, including: RMSE (Root Mean Squared Error), MSE (Mean Squared Error), MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), R2 (R-squared) and Adjusted R2
    - To get a complete picture of the performance of the various models.
    - Since predicting the price accurately is very difficult we will see also how good the models are at predicting whether the price will go up or down.
      * We compute whether each prediction is correct (1) or not (0)
      * Then we count the number of correct prediction
      * Finally we compute the percentage of accuracy of the model
  + **Pipeline**
    - Several types of regression algorithms will be used, including: Linear Regression, Generalized Linear Regression, Random Forest Regressor and Gradient Boosting Tree Regressor to see their differences and how they perform in the various stages of training / validation and testing.
    - In order to train and validate the model I will try several approaches:
      * Default without normalization: Make predictions using the chosen base model
      * Default with normalization: Like the previous one but features are normalized
    - Then the features that gave on average the most satisfactory results (for each model) are chosen and proceeded with:
      * Hyperparameter tuning: Researching the best parameters to use
      * Cross Validation: Validate the performance of the model with the chosen parameters
    - If the final results are satisfactory, the model will be trained on the whole train / validation set and saved to later make predictions on the test set.
    - For each approach the train / validation set will be split according to the chosen splitting method (in order to figure out which one works best for our problem):
      * Block time series splits: Involves dividing the time series into blocks of equal length, and then using each block as a separate fold for cross-validation.
      * Walk forward time series splits: Involves using a sliding window approach to create the training and validation sets for each fold. The model is trained on a fixed window of historical data, and then validated on the next observation in the time series. This process is repeated for each subsequent observation, with the window sliding forward one step at a time.
      * Single time series split Involves dividing the time series considering as validation set a narrow period of time and as train set everything that happened before this period, in such a way as to best benefit from the trend in the short term.
  + **Train / validation results**
    - As we can see there have been improvements using the single splitting method, in fact taking accuracy into account I have that all models exceed 54% accuracy and in general it seems to me that RandomForest is the algorithm that performs best.
      * Since it gives the best results I decided to train the model based on this splitting method
* **Models testing** 
  + **Pipeline**
    - After loading the previously trained models on the whole train / validation set, the test set is divided into further mini-sets of 1 week, 15 days, 1 month and 3 months to see how the models' performance degrades as time increases.
  + **Results**
    - Random forest and gradient boosting tree are the ones that in general returned me lower RMSE and higher accuracy percentage
    - Taking into account the time frame considered, the lower it is the more the RMSE and accuracy have very good values (While as you consider larger time horizons the performance degrades)
* **Conclusions**
  + In conclusion we can say that yes, it is possible to get an idea of the price prediction of Bitcoin
  + The selected features were very helpful in reaching our goal
  + The different splitting methods gave us a general overview
  + The models used returned results that were not very satisfactory
  + What could be done in the future is to use additional features, try different approaches, or even implement NN