



JONES COLLEGE OF BUSINESS

Python for Data Science What is Machine Learning?



What is machine Learning?

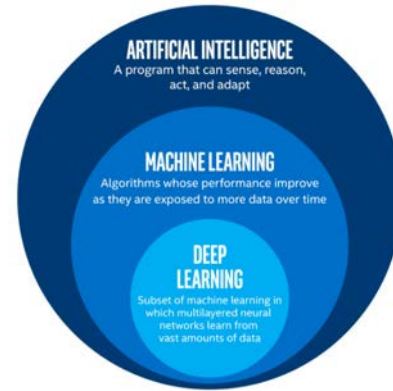
- **Machine learning** is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed.



Machine learning focuses on the development of computer programs that can access data and use it learn for themselves.

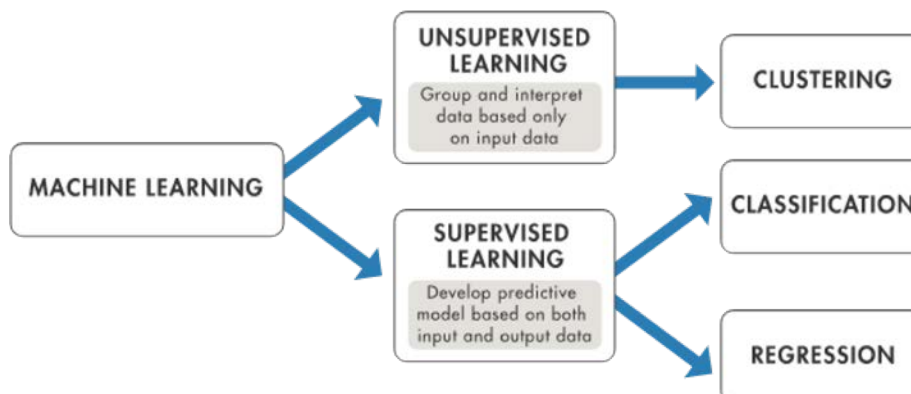
What is machine Learning?

- **Machine learning** is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed.

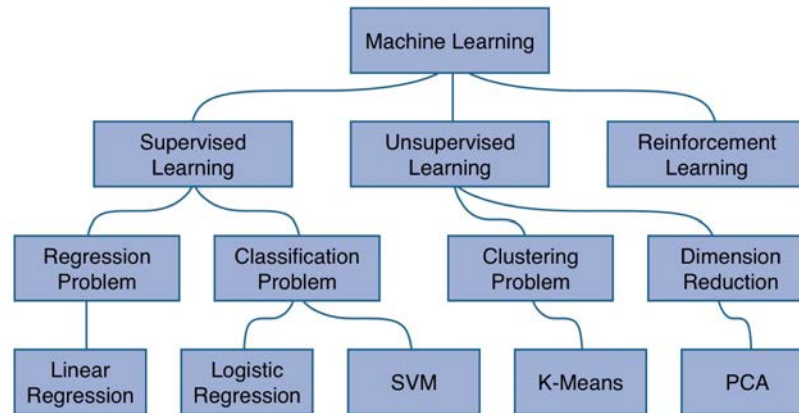


Machine learning focuses on the development of computer programs that can access data and use it learn for themselves.

Different types of ML

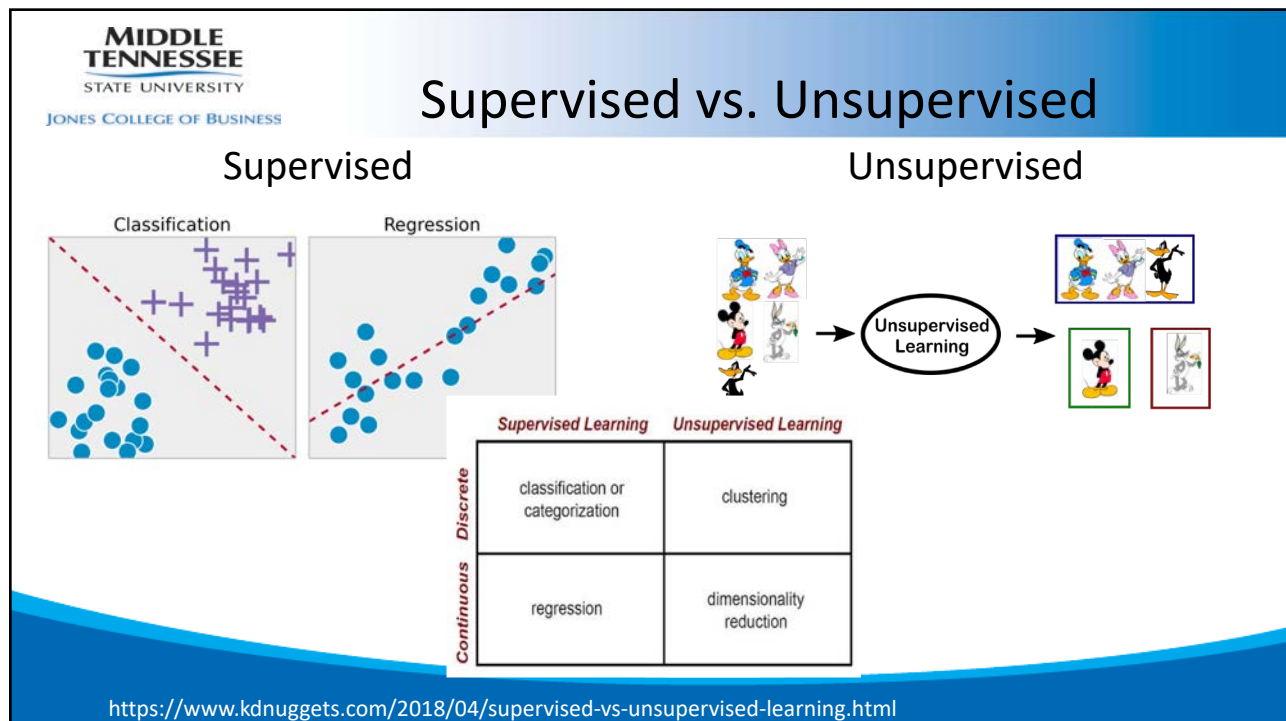
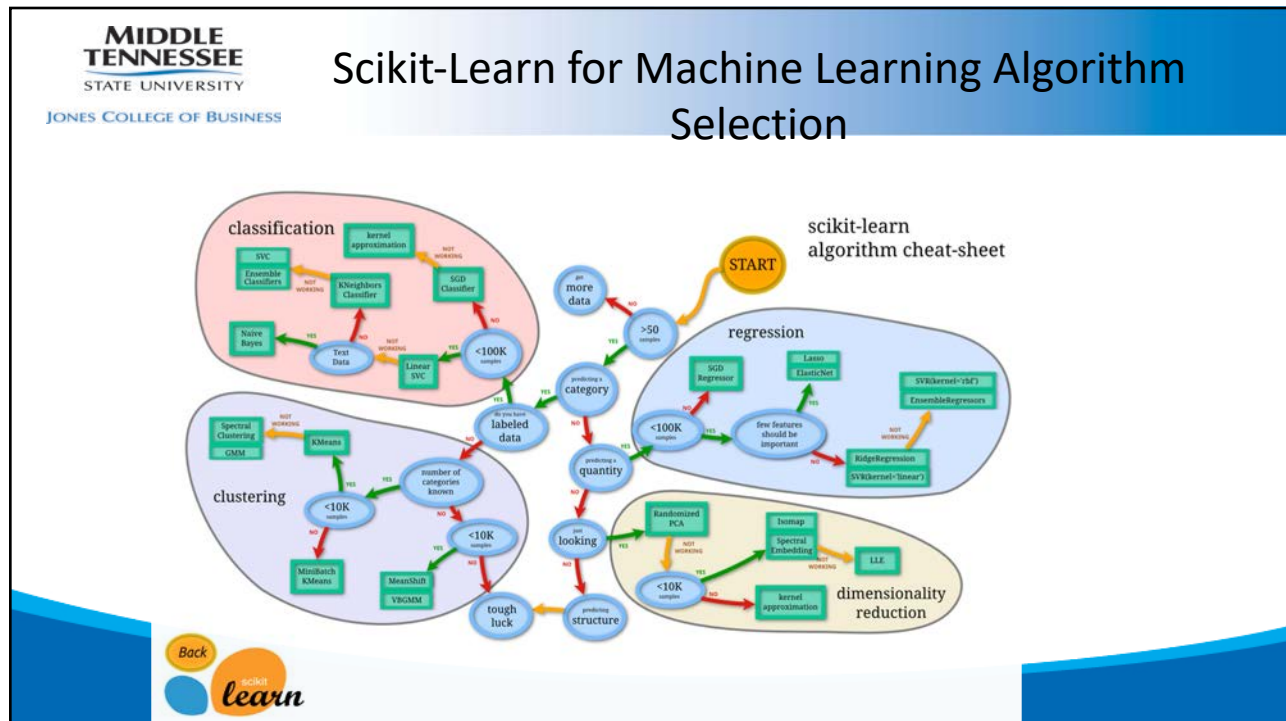


Different types



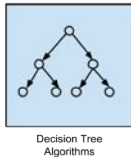
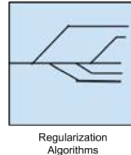
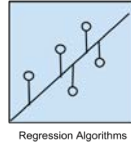
Machine Learning Algorithms Mind-Map



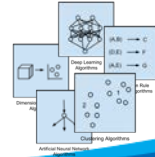
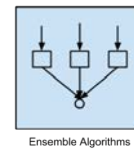
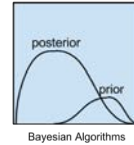


Types of Algorithms

- Regression Algorithms
 - Ordinary Least Squares Regression (OLSR)
 - Linear Regression
 - Logistic Regression
 - Stepwise Regression
- Regularization Algorithms
 - Ridge Regression
 - Least Absolute Shrinkage and Selection Operator (LASSO)
 - Elastic Net
- Decision Tree Algorithms
 - Classification and Regression Tree (CART)
 - Iterative Dichotomiser 3 (ID3)
 - Chi-squared Automatic Interaction Detection (CHAID)



- Bayesian Algorithms
 - Naive Bayes
 - Gaussian Naive Bayes
 - Multinomial Naive Bayes
- Ensemble Algorithms
 - Boosting
 - Bootstrapped Aggregation (Bagging)
 - AdaBoost
 - Gradient Boosting Machines (GBM)
 - Random Forest
- Clustering Algorithms
- Association Rule Learning Algorithms
- Dimensionality Reduction Algorithms
- Deep Learning Algorithms
- Artificial Neural Network Algorithms
- ...and many others



Top 10 Use Cases for Data Science & Machine Learning

HEALTHCARE:
Patient Diagnosis

FINANCE:
Fraud Detection

MANUFACTURING:
Anomaly Detection

RETAIL:
Inventory Optimization

GOVERNMENT:
Smarter Services

TRANSPORTATION:
Demand Forecasting

NETWORKS:
Intrusion Detection

E-COMMERCE:
Recommender Systems

MEDIA:
Interaction & Speed

EDUCATION:
Research Insight

What will we use?

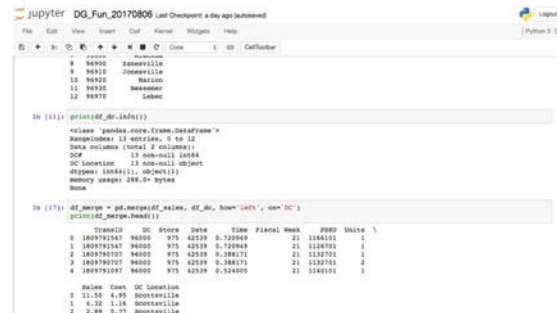
Anaconda

<https://anaconda.org/>



Jupyter Notebooks

<http://jupyter.org/>



mtsu.edu/dsi

`mt_dsi['using data for good'].max()`

Jupyter Notebooks

jupyter Apigian_Solution (autosaved)

File Edit View Insert Cell Kernel Widgets Help Trusted Python 3

Feature Scaling

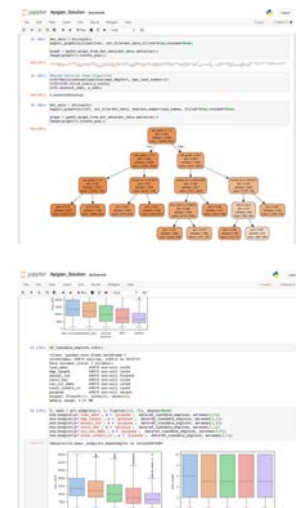
- StandardScaler
 - The StandardScaler assumes your data is normally distributed within each feature and will scale them such that the distribution is now centred around 0, with a standard deviation of 1.
$$\frac{x_i - \text{mean}(x)}{\text{std}(x)}$$
- MinMaxScaler
 - The MinMaxScaler is the probably the most famous scaling algorithm, and follows the following formula for each feature:
$$\frac{x_i - \min(x)}{\max(x) - \min(x)}$$

From <http://benalexkeen.com/feature-scaling-with-scikit-learn/>

```
In [66]: X_train.head()
```

```
Out[66]:
```

| | loan_amnt | term | sub_grade | emp_length | annual_inc | delinq_2yrs | mths_since_last_delinq | open_acc | pub_rec | revol_bal | tot_cur_debt | total_credit_rv |
|-------|-----------|------|-----------|------------|------------|-------------|------------------------|----------|---------|-----------|--------------|-----------------|
| 6972 | 22000 | 36 | 9 | 4 | 110000.0 | 0 | 54.0 | 13 | 0 | 7246 | ... | 0 |
| 22341 | 19750 | 60 | 25 | 10 | 50000.0 | 2 | 10.0 | 18 | 0 | 11456 | ... | 21200 |
| 2599 | 6925 | 60 | 22 | 4 | 35000.0 | 0 | 0.0 | 9 | 0 | 5896 | ... | 0 |
| 35251 | 30000 | 60 | 20 | 10 | 115000.0 | 0 | 0.0 | 6 | 0 | 21756 | ... | 25900 |
| 44831 | 20675 | 36 | 2 | 8 | 237000.0 | 0 | 48.0 | 12 | 0 | 10855 | ... | 18200 |



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Use of Python Libraries

http://chris35wills.github.io/courses/pydata_stack/

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How do you build a model?

- 1.
- 2.
- 3.
- 4.
- 5.
- 6.

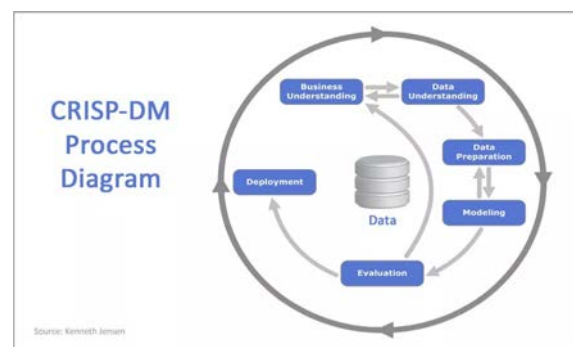
Modeling

Model Building Process

- | | |
|--|---------------------------|
| 1. Select a model | 1. Business Understanding |
| 2. Identify and select the data that fits that model | 2. Data Understanding |
| 3. Transform the data | 3. Data Preparation |
| 4. Identify a business problem | 4. Modeling |
| 5. Train/Test Split | 5. Evaluation |
| 6. Run Model | 6. Deployment |

Data Analysis Process

1. Business Understanding
 - a. Frame the problem and the REAL pain point
 - b. Available resources, problems, goals
2. Data Understanding
 - a. What data do you have available to you?
 - b. Setup your workspace with tools or applications
 - Programming – Jupyter notebooks for Python or R Studio for R
 - BI/spreadsheets – Excel – PowerPivot - Tableau
 - c. Import or download the data
 - d. View, explore, and summarize the data
3. Data Preparation
 - a. Clean up null values, outliers, mistakes
 - b. Construct new data, transform or feature engineering
 - c. Integrate and merge data
 - d. Format data (strings, integers, floats, etc.)
 - e. Create you X and y
4. Modeling
 - a. Split your data (Train/Test Split)
 - b. Setup models for machine learning/AI processes
 - c. Can include visuals, dashboards or reports



5. Evaluation
 - a. Fine tune your model
 - b. Create a report of the findings
6. Deployment of models

Appleton Lending Co

- **Operations**

- Over 80% of the loans provided by Appleton are personal. These loans are mostly made by borrowers in order to consolidate debt or pay off credit cards, but they may be provided for numerous reasons such as weddings, vacations, and for small businesses.

- **Strategy**

- Over the past two years, Appleton has provided over 3 billion dollars in loans. The company provides personal loans for amounts between \$1,000 and \$40,000 that can be repaid over time periods of 3 or 5 years. Appleton approves loans based on credit history, credit score, debt to income ratio (dti), and the amount of the loan applied for. Appleton is highly selective with the loans it accepts, with over an 80% denial rate over the past four years. This ensures that Appleton provides high quality opportunities for itself and for lenders.

Appleton Lending Co

- After some negative publicity at the board level, Appleton is looking to refocus its efforts on providing high quality loans. They are wanting to better understand their customers and most importantly, the difference between good loans and bad loans.
- After understanding the type of customers that they serve, they would like to improve the company's ability to predict borrowers who will default on loans. Additionally, Appleton is interested in predicting how much a borrower would be able to pay back, regardless of how large of a loan they have applied for.

Business Understanding

1. Business Understanding

- Available resources, problems, goals

2. Data Understanding

3. Data Preparation

4. Modeling

5. Evaluation

6. Deployment of models

- What are the available resources?
 - What are the key performance indicators (variables)?
- What are Appleton's expressed problems?
- What are Appleton's expressed and underlying goals?

What data do you have available?

Why is this data too much?

| Feature | Description | Feature | Description |
|---------------------|--|----------------------------|--|
| member_id | A unique Appleton assigned id for the borrower member. | dti | A ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested Appleton loan, divided by the borrower's self-reported monthly income. |
| loan_amnt | The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value. | delinq_2yrs | The number of 30+ days past due incidences of delinquency in the borrower's credit file for the past 2 years. |
| funded_amnt | The total amount committed to that loan at that point in time. | earliest_cr_line | The month the borrower's earliest reported credit line was opened. |
| funded_amnt_inv | The total amount committed by investors for that loan at that point in time. | inq_last_6mths | The number of inquiries in past 6 months (excluding auto and mortgage inquiries). |
| term | The number of payments on the loan. Values are in months and can be either 36 or 60. | mths_since_last_delinq | The number of months since the borrower's last delinquency. |
| int_rate | Interest Rate on the loan. | mths_since_last_record | The number of months since the last public record. |
| installment | The monthly payment owed by the borrower if the loan originates. | open_acc | The number of open credit lines in the borrower's credit file. |
| grade | Appleton assigned loan grade: A, B, C, D, etc. with A being the best. | pub_rec | Number of derogatory public records. |
| sub_grade | Appleton assigned loan subgrade: A1, A2, A3, etc. with A1 being the best. | revol_bal | Total credit revolving balance. |
| emp_title | The job title supplied by the Borrower when applying for the loan. | revol_util | Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credits. |
| emp_length | Employment length in years. Possible values are between 0 and 10 where 0 means less than one year and 10 means ten or more years. | total_acc | The total number of credit lines currently in the borrower's credit file. |
| home_ownership | The home ownership status provided by the borrower during registration. Our values are: RENT, OWN, MORTGAGE, OTHER. | initial_list_status | The initial listing status of the loan. Possible values are: W, F. |
| annual_inc | The self-reported annual income provided by the borrower during registration. | out_prncp | Remaining outstanding principal for total amount funded. |
| verification_status | Indicates if income was verified by Appleton, not verified, or if the income source was verified. | out_prncp_inv | Remaining outstanding principal for portion of total amount funded by investors. |
| issue_d | The month which the loan was funded. | total_pymnt | Payments received to date for total amount funded. |
| loan_status | Current status of the loan. | total_pymnt_inv | Payments received to date for portion of total amount funded by investors. |
| pymnt_plan | Indicates if a payment plan has been put in place for the loan. | total_rec_prncp | Principal received to date. |
| desc | Loan description provided by the borrower. | total_rec_int | Interest received to date. |
| purpose | A category provided by the borrower for the loan request. | total_rec_late_fee | Late fees received to date. |
| title | The loan title provided by the borrower. | recoveries | post charge off gross recovery. |
| zip_code | The first 3 numbers of the zip code provided by the borrower in the loan application. | collection_recovery_fee | post charge off collection fee. |
| addr_state | The state provided by the borrower in the loan application. | last_pymnt_d | Last month payment was received. |
| | | last_pymnt_amnt | Last total payment amount received. |
| | | next_pymnt_d | Next scheduled payment date. |
| | | last_credit_pull_d | The most recent month Appleton pulled credit for this loan. |
| | | collections_12_mths_ex_med | Number of collections in 12 months excluding medical collections. |
| | | mths_since_last_major_der | Months since most recent 90-day or worse rating. |
| | | policy_code | publicly available policy_code=1 new products not publicly available policy_code=2 |
| | | application_type | Indicates whether the loan is an individual application or a joint application with two co-borrowers. |
| | | acc_now_delinq | The number of accounts on which the borrower is now delinquent. |
| | | tot_coll_amt | Total collection amount ever owed. |
| | | tot_cur_bal | Total current balance of all accounts. |
| | | total_credit_rv | Total revolving high credit/credit limit. |
| | | loan_is_bad | True if borrower defaulted on loan. False if loan was good. |

• What is the RIGHT available data?

```
df_loandata = pd.read_csv('data/Loan_Data.csv', index_col = 0, header = 0)
df_loandata.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 49870 entries, 149512 to 4076727
Data columns (total 20 columns):
loan_amnt                49870 non-null int64
term                    49870 non-null int64
sub_grade               49870 non-null object
emp_length              49870 non-null int64
home_ownership          49870 non-null object
annual_inc              49870 non-null float64
purpose                 49870 non-null object
delinq_2yrs             49870 non-null int64
mths_since_last_delinq  21790 non-null float64
open_acc                49870 non-null int64
pub_rec                 49870 non-null int64
revol_bal               49870 non-null int64
total_acc               49865 non-null float64
collections_12_mths_ex_med 49870 non-null int64
mths_since_last_major_derog 49870 non-null int64
acc_now_delinq          49870 non-null int64
tot_coll_amt           49870 non-null int64
tot_cur_debt            49870 non-null int64
total_credit_rv         49870 non-null int64
loan_status             49870 non-null object
dtypes: float64(3), int64(13), object(4)
memory usage: 8.0+ MB
```

Supervised Learning Models

- Which tests will we conduct?
- Is it a bad loan?
 - Logistic Regression (prob.)
 - Decision Tree
 - Random Forest (ensemble)
- How much to loan?
 - Regression
 - Ridge Regression (predict)
 - Lasso Regression (sig. features)

Confusion Matrix

| | | Predictions | | |
|--------|---|-------------|------|-------|
| | | 0 | 1 | |
| Actual | 0 | 11354 | 1278 | 12632 |
| | 1 | 1798 | 527 | 2325 |
| | | 13152 | 1805 | |

| | | Predictions | | |
|--------|----------------|-------------|--------|-------|
| | | No | Affair | |
| Actual | Not a Bad Loan | TP | FN | 12632 |
| | Bad Loan | FP | TN | 2325 |
| | | 13152 | 1805 | |

Recall

| | | Predictions | | |
|--------|---|-------------|------|-------|
| | | 0 | 1 | |
| Actual | 0 | 11354 | 1278 | 12632 |
| | 1 | 1798 | 527 | 2325 |
| | | 13152 | 1805 | |

| | | Predictions | | |
|--------|----------------|-------------|--------|-------|
| | | No | Affair | |
| Actual | Not a Bad Loan | TP | FN | 12632 |
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| | | 13152 | 1805 | |

The recall is the ratio

- $tp / (tp + fn)$
- where tp is the number of true positives
- fn the number of false negatives.
- The recall is intuitively the ability of the classifier to find all the positive samples.
- $11354 / 12632 = 0.90$
- $1278 / 12632 = 0.23$

Precision

| | | Predictions | | |
|--------|---|-------------|------|-------|
| | | 0 | 1 | |
| Actual | 0 | 11354 | 1278 | 12632 |
| | 1 | 1798 | 527 | 2325 |
| | | 13152 | 1805 | |

The precision is the ratio:

- $tp / (tp + fp)$
- **tp** is the number of true positives
- **fp** the number of false positives.
- The precision is intuitively the ability of the classifier not to label as positive a sample that is negative.

$$11354 / 13152 = 0.86$$

$$1798 / 13152 = 0.29$$

| | | Predictions | | |
|--------|----------------|-------------|--------|-------|
| | | No | Affair | |
| Actual | Not a Bad Loan | TP | FN | 12632 |
| | Bad Loan | FP | TN | 2325 |
| | | 13152 | 1805 | |

F1

```
sklearn.metrics.f1_score(y_true, y_pred, labels=None, pos_label=1, average='binary', sample_weight=None)
```

[source]

Compute the F1 score, also known as balanced F-score or F-measure

The F1 score can be interpreted as a weighted average of the precision and recall, where an F1 score reaches its best value at 1 and worst score at 0. The relative contribution of precision and recall to the F1 score are equal. The formula for the F1 score is:

$$F1 = 2 * (precision * recall) / (precision + recall)$$

- $F1 = 2 * (0.86 * 0.90) / (0.86 + 0.90)$
- $F1 = 2 * (0.7452) / (1.76)$
- $F1 = 0.86$