# IDL TP Final scikit-learn Projet

## Charger les donnés

```
In [1]: import os
        import pandas as pd
In [2]: def load reviews(data dir):
                 reviews = []
                 labels = []
                 for label in ["pos", "neg"]:
                         directory = os.path.join(data dir, label)
                         for filename in os.listdir(directory):
                                  if filename.endswith(".txt"):
                                          file_path = os.path.join(directory, filename
                                          with open(file path, 'r', encoding='utf-8')
                                                   reviews.append(file.read())
                                                   labels.append(1 if label == "pos" el
                 return reviews, labels
In [3]: data dir = 'imdb smol'
        reviews, labels = load reviews(data dir)
        reviews df = pd.DataFrame({'review': reviews, 'label': labels})
In [4]: print("Nombre de données:", len(reviews df))
       Nombre de données: 602
In [5]: reviews df.head()
Out[5]:
                                                 review label
        0
             The production quality, cast, premise, authent...
                                                             1
               This is no art-house film, it's mainstream ent...
                                                             1
         2 Two great comedians in a great Neil Simon movi...
                                                             1
        3
             I'm a fan of TV movies in general and this was...
                                                             1
         4
                 Once upon a time in a castle..... Two little ...
                                                             1
In [6]: print("\nNombre de notes positives:", (reviews df['label'] == 1).sum())
        print("Nombre de notes négatives:", (reviews df['label'] == 0).sum())
       Nombre de notes positives: 301
       Nombre de notes négatives: 301
In [7]: print("\nInformations générales sur le DataFrame:")
        print(reviews df.info())
```

Index de la note de review: 307
Texte de la note de review:

\*Possible Spoiler\*<br /><br />'Return to Cabin by the Lake' is a useless mo vie. The acting was not good and the plot wasn't even remotely interesting. br /><br />'Cabin by the Lake' is a good TV movie. The sequel was not. Judd Nelson was very good in the first film and put a whole lot more into his cha racter than in this. It seemed as if HE wasn't even interested in doing the sequel. His acting was good but it could have been better. I really don't wa nt to comment on the rest of the cast because in my opinion, they're not eve n worth mentioning. But I'll do it. The character of Alison isn't even hardl y shown in the first part of the film. All of a sudden she's the center of a ttention next to Stanley Caldwell. The role didn't make sense and it should have been thought out a little better. Dahlia Salem was absolutely terrible. Her acting was way below decent and the casting people should have looked fo r somebody else, anybody else. The director, Mike, was a confusing characte r. He seemed to have a purpose for being there but it didn't seem like his d eath was necessary. The acting for this role was good, nothing great but bet ter than Salem's.<br /><br />The plot was real lousy if you think about it. Stanley, who is presumed dead, makes his way onto the set of 'Cabin by the L ake', the movie based on his script. He stumbles upon the director and in a short time, the director is dead and Stanley is running the show. Yeah, out of nowhere the crew is just going to let this stranger come into the picture and finish the film not knowing anything about him. There's some killings, n ot a whole lot, and the one's that are shown are ridiculous. One of the actr esses on the set gets electrocuted while filming a scene. Another character gets chewed up by a motorboat. And one gets tangled up in a plant before dro wning. These writers must have been hard up for excitement.<br /><br />I jus t have to say that I was not impressed with the filming of the movie. The wa y that it kept changing from looking low budget back to normal started to be come irritating very fast. Also, the new cabin by the lake was poorly create d. We aren't shown it but only in a few scenes, and the whole thing with the chain in the basement was useless. It worked in the first film only because we were shown the room a lot more, but it didn't work in this one.<br/>
<br/>br />There were too many characters in this sequel. All of them except for a fe w had no reason to be there. The acting of what little is showed was really bad and...they just didn't have a purpose in this movie.<br /><br />All in a ll, 'Return to Cabin by the Lake' is a sequel picking up from where the firs t left off. 'Cabin by the Lake' I can take but this was just not impressive. Judd Nelson should have avoided this one and so should you. It's nothing lik e the first and it went entirely too slow. Nothing happened in the first hou r and it continued to drag on for the second. Not to mention that the writin g was horrible. Put this on only if you need some help getting to sleep.<br /><br />So, we see that Stanley defies death and is still alive and well. By the way he talks, it sounds like there could be a possible third installment to a movie good just by itself. Quit throwing in sequels and we may be alrig ht!<br /><br />(Did the film makers not realize that they showed us how they filmed the lake scenes from the first one? They were all done in a tank. Nev er, never reveal the secrets of filming.)<br /><br /> Étiquette: Négative

Litquette. Negative

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Étiquette: Négative

Index de la note de review: 179 Texte de la note de review:

Caught the tail end of this movie channel surfing through the cable movie c hannels, and was so intrigued I sought out the next showing.<br/>
/>cbr />I re ally didn't know what to expect after reading the program summary, but I cam e away from this movie feeling quite disturbed and distressed. It also gave me as adult who attended high school in the 80's, a little better insight in to what our kids have to contend with these days.<br/>
/>The fact that y ou don't see the shooting only adds to the chillness of the plot. To see bot h child and adult alike struggle to comprehend and come to terms with the se nseless shootings was at times overwhelming. And will admit that I shed quit e a few tears throughout.<br/>
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seek out to what, however I am sure glad I did see it.

Étiquette: Positive

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Étiquette: Positive

Index de la note de review: 344
Texte de la note de review:

Amateur, no budget films can be surprisingly good ... this however is not o ne of them.<br/>
<br/>
/><br/>Ah, another Brad Sykes atrocity. The acting is hideou s, except for Emmy Smith who shows some promise. The camera "direction" need s serious reworking. And no more "hold the camera and run" gimmicks either; it just doesn't work. The special effects are unimaginative, there's a probl em when the effect can be identified in real time. If you're going to rip of f an ear, please don't let us see the actor's real ear beneath the blood. Th e scenery is bland and boring (same as Mr. Sykes other ventures), and the mu sic is a cross between cheap motel porn and really bad guitar driven metal (see the scenery comment).<br /><br />Did I mention the lack of any real plo t, or character development? Apparently, the scriptwriter didn't.<br /><br / >Whoever is funding this guy ... please stop. I've seen some of his other "h ome movies" (which I will not plug) and they are just as bad. Normally, a "d irector" will grow and learn from his previous efforts ... not this guy. I t's one thing to be an amateur filmmaker, but anyone can be a hack.<br/> />Definitely not even a popcorn film ... of course, chewing on popcorn kerne ls would be less painful than this effort.<br /><br />Award: The worst ever military push-ups in a film.

Étiquette: Négative

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Index de la note de review: 94 Texte de la note de review:

"Wisecracker," the biography of actor William Haines, offers a gratifying a necdote about the former star when he was past 70 and long retired from maki ng movies. The old gent was not sentimental and rarely watched his own film s, but in 1972 he was persuaded to attend a Los Angeles museum screening of SHOW PEOPLE, the late silent feature in which he co-starred with Marion Davi es. Beforehand, Haines was worried that this comedy would provoke the wrong kind of laughter, but he was pleasantly surprised (and no doubt relieved) at how well it held up and how much the young audience enjoyed it. Watch the fi lm today and you can see why: SHOW PEOPLE is a delightful Hollywood satire t hat retains its charm because it lampoons its targets with wit and flair, ye t without malice. It's still funny and its satirical points still resonate. Needless to say, the technology of movie-making has changed vastly since the silent days, but the pretensions and follies of the filmmakers themselves ha ven't changed all that much.<br /><br />SHOW PEOPLE also stands as the best surviving work of Marion Davies, a first-rate comic performer who deserves a prominent place in the pantheon of great comediennes. Where her career was c oncerned Davies was both blessed and cursed by the patronage of her paramou r, the newspaper magnate William Randolph Hearst. It's well known that Hears t exerted enormous influence over Davies' choice of roles, and well known to o that, despite her gift for comedy, he preferred to see her play dignified heroines in period costume dramas. By the late '20s, for whatever reason, Ma rion was permitted to strut her stuff in several exuberant light comedies (i ncluding THE RED MILL and THE PATSY), but SHOW PEOPLE, directed by the great King Vidor, stands as her most enjoyable showcase. William Haines gives an e ngaging, likable performance as her boyfriend and co-star Billy Boone, but t his is the leading lady's show all the way.<br />dr />Marion plays Southern belle Peggy Pepper, an aspiring actress who storms Hollywood accompanied by her father, determined to become a movie star. (Her dad Colonel Pepper is pl ayed by actor/director Dell Henderson, a veteran of Griffith's Biograph dram as who∎coincidentally?∎resembled Hearst!) One of Marion's funniest bits, ofte n excerpted elsewhere, is her audition at the Comet Studio casting office. W hile Dad helpfully suggests emotions to portray ("Sorrow! . . . Joy!") and d rops a handkerchief across her face, Peggy assumes the appropriate expressio n and posture. She's hired, only to discover that Comet makes low-brow comed ies, the kind of comedies where people squirt each other with seltzer and in ept cops tumble over each other racing to the rescue. Of course, Comet is in tended as a take-off of Mack Sennett's Keystone, but the true nature of the satire becomes clear as the story unfolds. As Peggy Pepper rises in the movi e star hierarchy she leaves Comet for the more prestigious High Art Studio, assuming the name "Patricia Peppoire" as more befitting her new station in l ife as a serious actress. At some point it may occur to us (as it surely did to viewers in 1928) that Davies' rival Gloria Swanson started out in Keyston e comedies before rising to prominence in serious dramas for Cecil B. DeMill e. And as Miss Peppoire takes herself more and more seriously, giving the hi gh-hat treatment to former colleagues such as lowly comic Billy Boone, Davie s' performance takes on an element of wicked parody seemingly aimed squarely at Swanson herself. This is especially notable during an interview sequence, when Miss Peppoire's spokesman spouts pretentious nonsense while the star de

livers a spot-on impersonation of Swanson. I suppose this was intended as a friendly spoof, but I have to wonder how friendly relations were between Glo ria and Marion after this movie was released.<br/>
FEOPLE is a delicious treat for buffs, who will relish the parade of star ca meos throughout. Charlie Chaplin contributes a nice bit, sans makeup and loo king quite distinguished, eagerly seeking Patricia Peppoire's autograph! (An d in a show of good sportsmanship Marion Davies herself puts in a self-mocking cameo appearance, evening the score for poking fun at Swanson by poking fun at herself.) This is a silent film that viewers not especially attuned to silents might appreciate, at least those viewers with a taste for movies about the movie business. SHOW PEOPLE surely belongs in the company of such classics as SUNSET BOULEVARD and SINGIN' IN THE RAIN, among Hollywood's most expertly produced, enjoyable exercises in amused self-examination. Étiquette: Positive

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Étiquette: Positive

Index de la note de review: 524
Texte de la note de review:

:Spoilers:<br /><br />I was very disappointed in Love's Abiding Joy. I had been waiting a really long time to see it and I finally got the chance when it re-aired Thursday night on Hallmark. I love the first three "Love" movies but this one was nothing like I thought it was going to be. The whole movie was sad and depressing, there were way to many goofs, and the editing was ve ry poor - to many scenes out of context. I also think the death of baby Kath y happened way to soon and Clarks appearance in the movie just didn't seem t o fit. It seemed like none of the actors really wanted to be there - they we re all lacking emotion. There seemed to be no interaction between Missie and Willie at all.<br /><br />I think the script writers should have went more b y the book. It seems like every movie that's been made so far just slips fur ther and further away from Janette Oke's writings. I mean in the movie they never mentioned a thing about the mine and the two boys or Clark getting hur t because of it. And I think Missie and Willies reactions to Kathy's death c ould have been shown and heard rather than just heard.<br /><br />out of the four movies that have been made so far I'd have to say that Love's Abiding J oy is my least favorite. I hope with the next four movies that more of the b ook is followed and if Clarks character is in them I hope he's got a bigger part and I hope his part isn't so bland. I also hope there is more of Scotti e and Cookie and maybe even Marty but who knows what the script writers will have in store next.

Étiquette: Négative

Index de la note de review: 524
Texte de la note de review:

:Spoilers:<br/>
'>spoilers:<br/>
'<br/>
'>spoilers:<br/>
'<br/>
'>spoilers:<br/>
'<br/>

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Étiquette: Négative

### Vectorisation

## Entraînement

### 1. Logistic Regression

```
model = LogisticRegression(random state=42)
                 model.fit(X train, y train)
                 y pred = model.predict(X test)
                 print("Accuracy:", accuracy score(y test, y pred))
                 print("Classification Report:\n", classification report(y test, y pr
In [17]: train and evaluate(features, reviews df['label'])
        Accuracy: 0.8543046357615894
        Classification Report:
                      precision recall f1-score
                                                      support
                  0
                          0.81
                                    0.88
                                              0.85
                                                          68
                  1
                          0.90
                                    0.83
                                              0.86
                                                          83
                                              0.85
                                                         151
            accuracy
           macro avg
                          0.85
                                    0.86
                                              0.85
                                                         151
        weighted avg
                          0.86
                                    0.85
                                              0.85
                                                         151
In [18]: train and evaluate(features count, reviews df['label'])
        Accuracy: 0.8079470198675497
        Classification Report:
                      precision recall f1-score
                                                      support
                  0
                          0.79
                                   0.78
                                              0.79
                                                          68
                  1
                          0.82
                                    0.83
                                              0.83
                                                          83
                                              0.81
                                                         151
            accuracy
                          0.81
                                    0.81
                                              0.81
                                                         151
           macro avq
        weighted avg
                          0.81
                                    0.81
                                              0.81
                                                         151
```

#### 2. SVM & GridSearchCV

```
Accuracy: 1.0
        Classification Report:
                       precision
                                    recall f1-score
                                                      support
                                     1.00
                                               1.00
                   0
                           1.00
                                                          301
                   1
                           1.00
                                     1.00
                                               1.00
                                                          301
                                               1.00
                                                          602
            accuracy
           macro avg
                           1.00
                                     1.00
                                               1.00
                                                          602
        weighted avg
                           1.00
                                     1.00
                                               1.00
                                                          602
In [22]: train and evaluate svm(features count, reviews df['label'], features count,
        Fitting 5 folds for each of 16 candidates, totalling 80 fits
        Best parameters: {'C': 100, 'gamma': 'auto', 'kernel': 'rbf'}
        Accuracy: 1.0
        Classification Report:
                       precision
                                    recall f1-score
                                                      support
                           1.00
                                     1.00
                                               1.00
                                                          301
                   0
                   1
                           1.00
                                     1.00
                                               1.00
                                                          301
            accuracy
                                               1.00
                                                          602
                                               1.00
                                                          602
                           1.00
                                     1.00
           macro avg
        weighted avg
                           1.00
                                     1.00
                                               1.00
                                                          602
         3. Random Forest
In [23]: from sklearn.ensemble import RandomForestClassifier
In [24]: def train and evaluate rf(features, labels):
                 X train, X test, y train, y test = train test split(features, labels
                 model = RandomForestClassifier(n estimators=100, random state=42)
                 model.fit(X train, y train)
                 y pred = model.predict(X test)
                 print("Accuracy:", accuracy_score(y_test, y_pred))
                 print("Classification Report:\n", classification report(y test, y pr
In [25]: train and evaluate rf(features, reviews df['label'])
        Accuracy: 0.7549668874172185
        Classification Report:
                       precision
                                    recall f1-score
                                                       support
                   0
                           0.70
                                     0.81
                                               0.75
                                                          68
                   1
                           0.82
                                     0.71
                                               0.76
                                                          83
                                               0.75
                                                          151
            accuracy
                           0.76
                                     0.76
                                               0.75
                                                          151
           macro avg
        weighted avg
                           0.76
                                     0.75
                                               0.76
                                                          151
```

Fitting 5 folds for each of 16 candidates, totalling 80 fits Best parameters: {'C': 10, 'gamma': 'scale', 'kernel': 'rbf'}

```
Accuracy: 0.7549668874172185
        Classification Report:
                       precision
                                    recall f1-score
                                                       support
                           0.68
                                     0.87
                                               0.76
                   0
                                                           68
                   1
                           0.86
                                     0.66
                                               0.75
                                                           83
                                               0.75
            accuracy
                                                          151
                                               0.75
                           0.77
                                     0.77
                                                          151
           macro avg
        weighted avg
                           0.78
                                     0.75
                                               0.75
                                                          151
         4. Naive Bayes
In [27]: from sklearn.naive bayes import MultinomialNB
In [28]: def train and evaluate nb(features, labels):
                 X train, X test, y train, y_test = train_test_split(features, labels
                 model = MultinomialNB()
                 model.fit(X train, y train)
                 y_pred = model.predict(X test)
                 print("Accuracy:", accuracy_score(y_test, y_pred))
                 print("Classification Report:\n", classification report(y test, y pr
In [29]: train_and_evaluate_nb(features, reviews_df['label'])
        Accuracy: 0.8145695364238411
        Classification Report:
                       precision
                                    recall f1-score
                                                       support
                           0.74
                                     0.91
                                               0.82
                                                           68
                   0
                           0.91
                                     0.73
                                               0.81
                                                           83
                                               0.81
                                                          151
            accuracy
                           0.82
                                     0.82
                                               0.81
                                                          151
           macro avg
        weighted avg
                           0.83
                                     0.81
                                               0.81
                                                          151
In [30]: train and evaluate nb(features count, reviews df['label'])
        Accuracy: 0.8410596026490066
        Classification Report:
                                    recall f1-score
                       precision
                                                       support
                                     0.91
                                               0.84
                                                           68
                   0
                           0.78
                                                           83
                   1
                           0.92
                                     0.78
                                               0.84
                                               0.84
                                                          151
            accuracy
                           0.85
                                     0.85
                                               0.84
                                                          151
           macro avg
        weighted avg
                           0.85
                                     0.84
                                               0.84
                                                          151
```

In [26]: train and evaluate rf(features count, reviews df['label'])

#### 5. Decision Tree

```
In [31]: from sklearn.tree import DecisionTreeClassifier
In [32]: def train and evaluate dt(features, labels):
                 X train, X test, y train, y test = train test split(features, labels
                 model = DecisionTreeClassifier(random state=42)
                 model.fit(X train, y train)
                 y pred = model.predict(X test)
                 print("Accuracy:", accuracy score(y test, y pred))
                 print("Classification Report:\n", classification report(y test, y pr
In [33]: train and evaluate dt(features, reviews df['label'])
        Accuracy: 0.6622516556291391
        Classification Report:
                       precision recall f1-score
                                                      support
                   0
                           0.62
                                    0.66
                                               0.64
                                                           68
                   1
                           0.71
                                     0.66
                                               0.68
                                                           83
                                               0.66
                                                          151
            accuracy
                           0.66
                                     0.66
                                               0.66
                                                          151
           macro avg
                                               0.66
                                                          151
        weighted avg
                           0.67
                                     0.66
In [34]: train and evaluate dt(features count, reviews df['label'])
        Accuracy: 0.6291390728476821
        Classification Report:
                       precision recall f1-score
                                                       support
                   0
                           0.58
                                     0.63
                                               0.61
                                                           68
                           0.68
                                     0.63
                                               0.65
                                                           83
                                               0.63
                                                          151
            accuracy
                                               0.63
                                                          151
                           0.63
                                     0.63
           macro avg
        weighted avg
                           0.63
                                     0.63
                                               0.63
                                                          151
         6. K-Nearest Neighbors
In [35]: from sklearn.neighbors import KNeighborsClassifier
In [36]: def train_and_evaluate_knn(features, labels):
                 X train, X test, y train, y test = train test split(features, labels
                 model = KNeighborsClassifier()
```

```
In [37]: train_and_evaluate_knn(features, reviews_df['label'])
```

print("Accuracy:", accuracy score(y test, y pred))

print("Classification Report:\n", classification\_report(y\_test, y\_pr

model.fit(X\_train, y\_train)
y pred = model.predict(X test)

Accuracy: 0.8675496688741722 Classification Report: precision recall f1-score

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0            | 0.85      | 0.85   | 0.85     | 68      |
| 1            | 0.88      | 0.88   | 0.88     | 83      |
| accuracy     |           |        | 0.87     | 151     |
| macro avg    | 0.87      | 0.87   | 0.87     | 151     |
| weighted avg | 0.87      | 0.87   | 0.87     | 151     |

In [38]: train\_and\_evaluate\_knn(features\_count, reviews\_df['label'])

Accuracy: 0.6291390728476821

Classification Report:

|              | precision | recall | fl-score | support |
|--------------|-----------|--------|----------|---------|
| 0            | 0.60      | 0.53   | 0.56     | 68      |
| 1            | 0.65      | 0.71   | 0.68     | 83      |
| accuracy     |           |        | 0.63     | 151     |
| macro avg    | 0.62      | 0.62   | 0.62     | 151     |
| weighted avg | 0.63      | 0.63   | 0.63     | 151     |

#### 7. XGBoost

```
In [39]: from xgboost import XGBClassifier
```

```
In [41]: train_and_evaluate_xgb(features, reviews_df['label'])
```

Accuracy: 0.7417218543046358

Classification Report:

```
precision recall f1-score
                                              support
           0
                  0.71
                            0.72
                                      0.72
                                                  68
                                      0.76
           1
                  0.77
                            0.76
                                                  83
                                      0.74
                                                 151
    accuracy
   macro avg
                  0.74
                            0.74
                                      0.74
                                                 151
                                      0.74
weighted avg
                  0.74
                            0.74
                                                 151
```

```
In [42]: train_and_evaluate_xgb(features_count, reviews_df['label'])
```

```
Accuracy: 0.7483443708609272
Classification Report:
                           recall f1-score
               precision
                                              support
                   0.70
                            0.76
                                       0.73
                                                  68
           0
           1
                   0.79
                            0.73
                                       0.76
                                                   83
                                       0.75
                                                  151
    accuracy
                                       0.75
                   0.75
                             0.75
                                                  151
   macro avq
weighted avg
                   0.75
                            0.75
                                       0.75
                                                  151
```

## **Evaluation**

```
In [43]: comparison data = {
             "Model": [].
             "Vectorization": [],
             "Accuracy": [],
             "Precision (macro)": [],
             "Recall (macro)": [],
             "F1-score (macro)": [],
In [44]: def add to comparison(model name, vectorization, accuracy, report):
                 """Add data to the comparison table."""
                 comparison data["Model"].append(model name)
                 comparison data["Vectorization"].append(vectorization)
                 comparison data["Accuracy"].append(accuracy)
                 comparison data["Precision (macro)"].append(report["macro avg"]["pre
                 comparison_data["Recall (macro)"].append(report["macro avg"]["recall
                 comparison data["F1-score (macro)"].append(report["macro avg"]["f1-s
In [45]: def run and add to comparison(features, labels, model name, model, vectorize
                 """Run the model and add it to the comparison table."""
                 X train, X test, y train, y test = train test split(features, labels
                 model.fit(X train, y train)
                 y pred = model.predict(X test)
                 accuracy = accuracy_score(y_test, y_pred)
                 report = classification report(y test, y pred, output dict=True)
                 add to comparison(model name, vectorization type, accuracy, report)
In [46]:
         run and add to comparison(features, reviews df['label'], "Logistic Regressic
         run and add to comparison(features count, reviews df['label'], "Logistic Red
         run and add to comparison(features, reviews df['label'], "Random Forest", Ra
         run and add to comparison(features count, reviews df['label'], "Random Fores
         run and add to comparison(features, reviews df['label'], "Naive Bayes", Mult
         run and add to comparison(features count, reviews df['label'], "Naive Bayes"
         run and add to comparison(features, reviews df['label'], "SVM", SVC(), "TF-I
         run and add to comparison(features count, reviews df['label'], "SVM", SVC(),
         run and add to comparison(features, reviews df['label'], "Decision Tree", De
```

run\_and\_add\_to\_comparison(features\_count, reviews\_df['label'], "Decision Tre
run\_and\_add\_to\_comparison(features, reviews\_df['label'], "KNN", KNeighborsCl
run\_and\_add\_to\_comparison(features\_count, reviews\_df['label'], "KNN", KNeigh
run\_and\_add\_to\_comparison(features, reviews\_df['label'], "XGBoost", XGBClass
run\_and\_add\_to\_comparison(features\_count, reviews\_df['label'], "XGBoost", XG

In [47]: comparison\_df = pd.DataFrame(comparison\_data)
 comparison\_df.head(20)

#### Out[47]:

| : |    | Model                  | Vectorization | Accuracy | Precision<br>(macro) | Recall<br>(macro) | F1-score<br>(macro) |
|---|----|------------------------|---------------|----------|----------------------|-------------------|---------------------|
|   | 0  | Logistic<br>Regression | TF-IDF        | 0.854305 | 0.853457             | 0.856839          | 0.853785            |
|   | 1  | Logistic<br>Regression | Count         | 0.807947 | 0.806237             | 0.805369          | 0.805766            |
|   | 2  | Random<br>Forest       | TF-IDF        | 0.754967 | 0.757823             | 0.759833          | 0.754795            |
|   | 3  | Random<br>Forest       | Count         | 0.754967 | 0.768768             | 0.765149          | 0.754795            |
|   | 4  | Naive Bayes            | TF-IDF        | 0.814570 | 0.824271             | 0.823352          | 0.814561            |
|   | 5  | Naive Bayes            | Count         | 0.841060 | 0.845246             | 0.847449          | 0.840997            |
|   | 6  | SVM                    | TF-IDF        | 0.854305 | 0.856340             | 0.859497          | 0.854145            |
|   | 7  | SVM                    | Count         | 0.761589 | 0.762454             | 0.753898          | 0.755927            |
|   | 8  | Decision<br>Tree       | TF-IDF        | 0.662252 | 0.660783             | 0.662208          | 0.660764            |
|   | 9  | Decision<br>Tree       | Count         | 0.629139 | 0.628203             | 0.629429          | 0.627817            |
|   | 10 | KNN                    | TF-IDF        | 0.867550 | 0.866230             | 0.866230          | 0.866230            |
|   | 11 | KNN                    | Count         | 0.629139 | 0.624176             | 0.620128          | 0.620330            |
|   | 12 | XGBoost                | TF-IDF        | 0.741722 | 0.739219             | 0.739812          | 0.739482            |
|   | 13 | XGBoost                | Count         | 0.748344 | 0.747455             | 0.749823          | 0.747447            |
|   |    |                        |               |          |                      |                   |                     |

In [ ]: