Projet FDA:
Video popularity prediction

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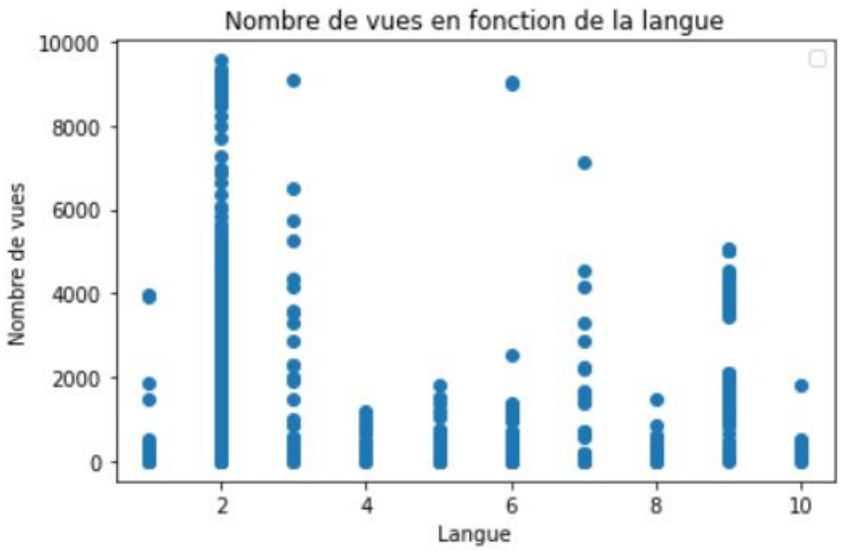
Présentation du Challenge

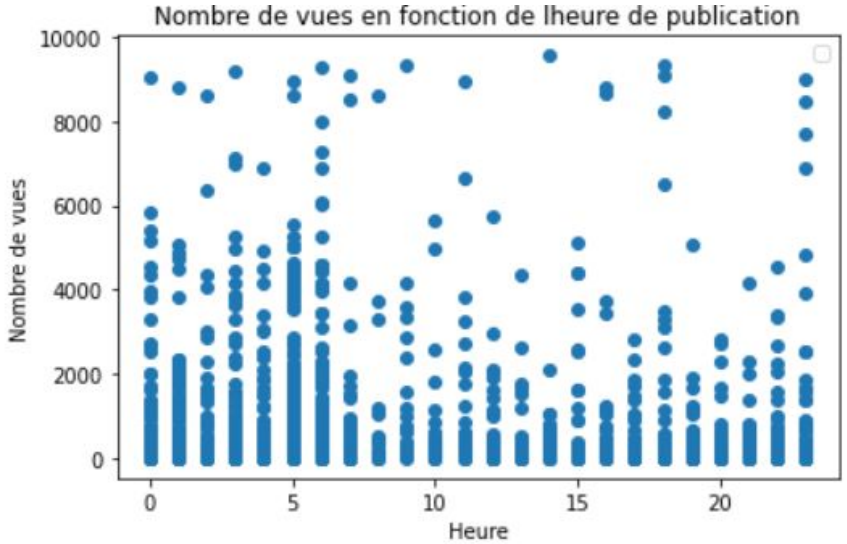
- Prédire le nombre de vues d'une vidéo

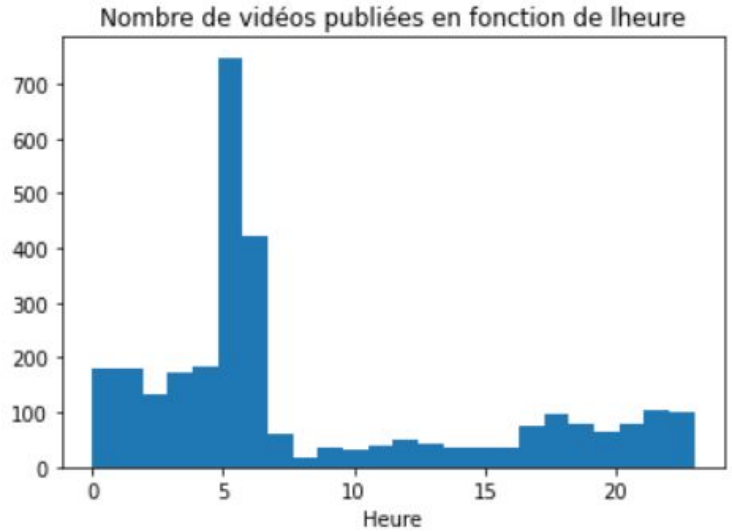
- 4 jeux de données
  - meta_data
  - image_df
  - title_df
  - desc_df

Quelques visualisations des données

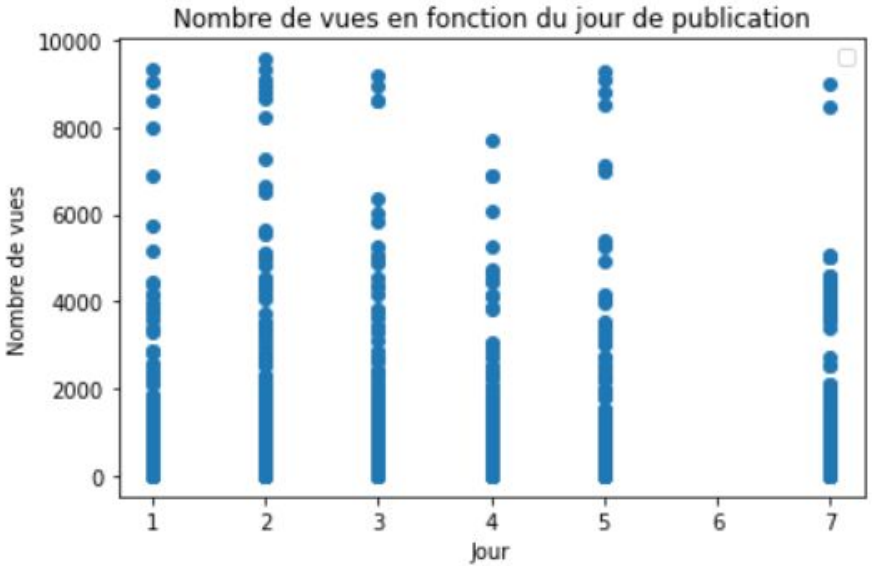


Quelques visualisations des données

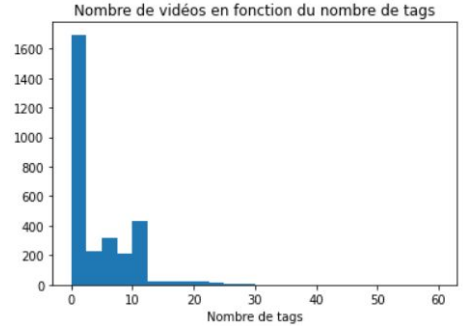


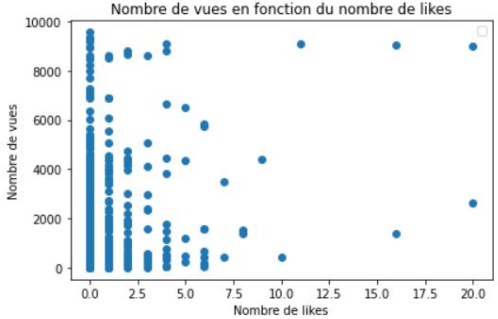


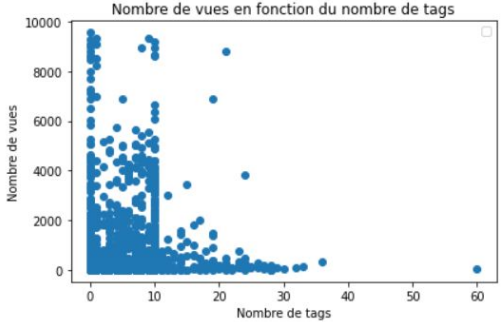
Quelques visualisations des données



Quelques visualisations des données







Traitement des données

- One hot encoding

emb_False	emb_True	prt_False	prt_True	prt_a_False	prt_a_True	Ing_1	Ing_2	Ing_3	Ing_4	Ing_5	Ing_6	Ing_7	Ing_8	Ing_9	Ing_10
0	1	0	1	1	0	0	0	1	0	0	0	0	0	0	0
0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0
0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0
0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0
0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0

Traitement des données

- Cyclical feature encoding

sin_hour	cos_hour	cos_day	sin_day
1.0	6.123234e-17	-0.222521	-0.974928
1.0	6.123234e-17	-0.222521	-0.974928
1.0	6.123234e-17	-0.222521	-0.974928
1.0	6.123234e-17	-0.222521	-0.974928
1.0	6.123234e-17	-0.222521	-0.974928

$$x_{sin} = \sin\left(\frac{2 * \pi * x}{\max(x)}\right)$$

$$x_{cos} = \cos\left(\frac{2 * \pi * x}{\max(x)}\right)$$

Traitement des données

- Feature selection avec Lasso regularization

Entrée [88]:
```
y = metadata['views']
x = image.loc[:, image.columns != 'comp_id']
```

Entrée [66]:
```
model = SelectFromModel(LogisticRegression(C=1, penalty='l1', solver='liblinear'))

model.fit(x, y)
model_index = model.get_support()

count = collections.Counter(model.get_support())
count
```

Out[66]:
```
Counter({False: 2742, True: 1258})
```

Modèles classiques

- Régression Linéaire Multiple

Entrée [73]:
```
std_scale = preprocessing.StandardScaler().fit(X_concat_train)
X_train_std = std_scale.transform(X_concat_train)
X_test_std = std_scale.transform(X_concat_test)
```

Entrée [79]:
```
# Entraînement
linearReg = LinearRegression().fit(X_train_std,y_concat_train)

# Test et évaluation
y_pred_linearReg = linearReg.predict(X_test_std)
print(evaluation(y_concat_test,y_pred_linearReg))
```

```
0.8150072853099513
```

Modèles classiques

- SVR

SVR

Entrée [77]:

```
for k in ['linear','poly','rbf','sigmoid']:
    svr = svm.SVR(kernel=k)
    svr.fit(X_train_std, y_concat_train)
    y_pred_svr = svr.predict(X_test_std)
    print(evaluation(y_concat_test,y_pred_svr))
```

```
0.8682720826389111
0.8610071312343667
0.8609954247080754
0.8610273368360938
```

Modèles classiques

- Arbre de décision

Entrée [80]:
```
# Entraînement
model_tree = tree.DecisionTreeRegressor()
model_tree.fit(X_concat_train, y_concat_train)

# Test et évaluation
y_pred_tree = model_tree.predict(X_concat_test)
print(evaluation(y_concat_test,y_pred_tree))
```

```
0.8446131273380897
```

Modèles classiques

- Forêt aléatoire

Forêt aléatoire

Entrée [81]:
```
# Entraînement
model_rf = RandomForestRegressor()
model_rf.fit(X_concat_train, y_concat_train)

# Test et évaluation
y_pred_rf= model_rf.predict(X_concat_test)
print(evaluation(y_concat_test,y_pred_rf))
```

```
0.8776789435673219
```

Autres modèles

- Lasso
- Ridge
- XGBoost
- LightGBM
- CatBoost

Lasso

```
# Entraînement
model_concat_lasso = Lasso(alpha = 100, max_iter = 30, tol = 0.1)
model_concat_lasso.fit(X_concat_train, y_concat_train)

# Test et évaluation
y_pred = model_concat_lasso.predict(X_concat_test)
print(evaluation(y_concat_test,y_pred))
```

```
0.8766135170259098
```

RIDGE

```
# Entraînement
model_concat_ridge = Ridge(alpha = 50, max_iter = 100, tol = 0.1)
model_concat_ridge.fit(X_concat_train, y_concat_train)

# Test et évaluation
y_pred = model_concat_ridge.predict(X_concat_test)
print(evaluation(y_concat_test,y_pred))
```

```
0.8353283037588435
```

XGBoost

```
# Entraînement
xgb_model = XGBRegressor()
xgb_model.fit(X_concat_train, y_concat_train)

# Test et évaluation
y_pred_xgb = xgb_model.predict(X_concat_test)
print(evaluation(y_concat_test,y_pred_xgb))
```

```
[19:04:31] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
0.8768094101211513
```

LightGBM

```
# Entraînement
model_lgbm = LGBMRegressor()
model_lgbm.fit(X_concat_train, y_concat_train)

# Test et évaluation
y_pred = model_lgbm.predict(X_concat_test)
print(evaluation(y_concat_test,y_pred))
```

```
0.8785824302244919
```

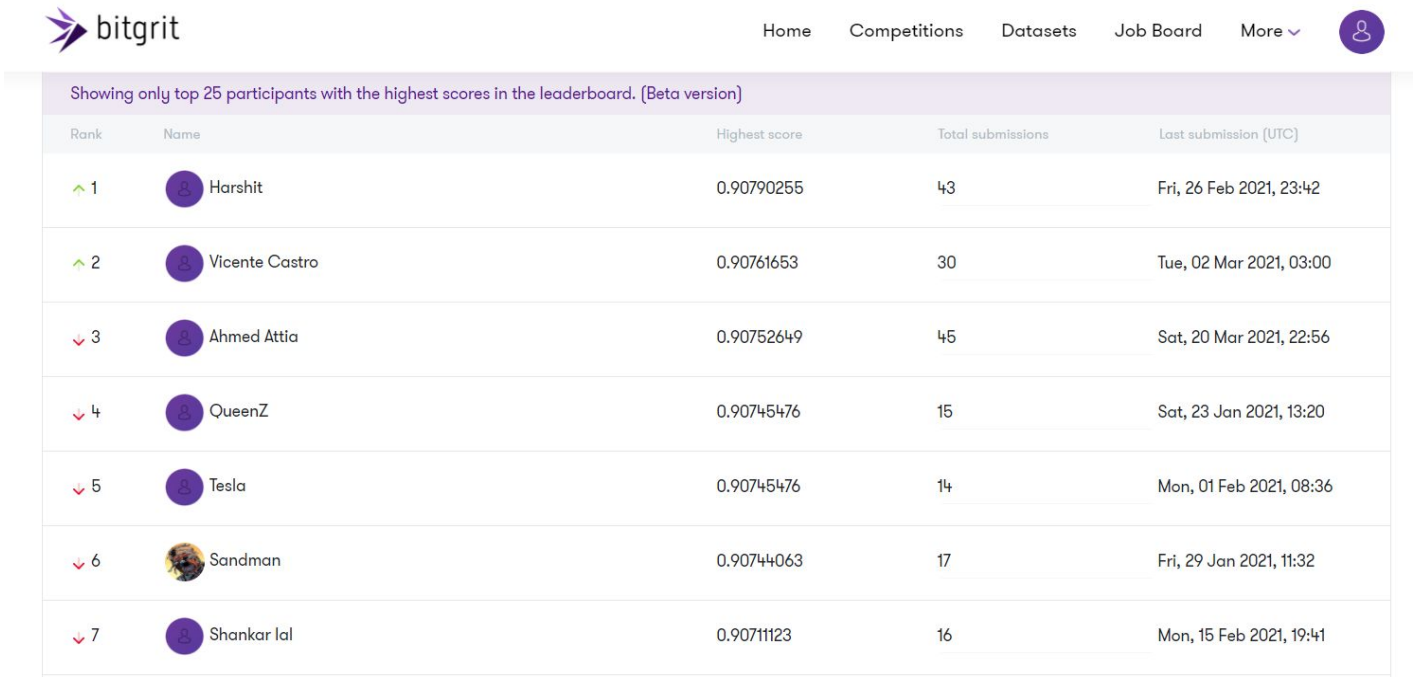
CatBoost

```
# Entraînement
model_catboost = CatBoostRegressor()
model_catboost.fit(X_concat_train, y_concat_train)
```

```
# Test et évaluation
y_pred_catboost = model_catboost.predict(X_concat_test)
print(evaluation(y_concat_test,y_pred_catboost))
```

```
0.8806404350492417
```

Résultats du concours



bitgrit

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Showing only top 25 participants with the highest scores in the leaderboard. (Beta version)

Rank	Name	Highest score	Total submissions	Last submission (UTC)
^ 1	Harshit	0.90790255	43	Fri, 26 Feb 2021, 23:42
^ 2	Vicente Castro	0.90761653	30	Tue, 02 Mar 2021, 03:00
v 3	Ahmed Attia	0.90752649	45	Sat, 20 Mar 2021, 22:56
v 4	QueenZ	0.90745476	15	Sat, 23 Jan 2021, 13:20
v 5	Tesla	0.90745476	14	Mon, 01 Feb 2021, 08:36
v 6	Sandman	0.90744063	17	Fri, 29 Jan 2021, 11:32
v 7	Shankar lal	0.90711123	16	Mon, 15 Feb 2021, 19:41

	solution_xgboost.csv 22.3 KB	Tue, 09 Mar 2021, 17:04	solution with xgboost	0.89141519
	solution_xgboost2.csv 21.59 KB	Tue, 09 Mar 2021, 17:41	xgboost with all the columns and without negative values	0.89764708
	solution_xgboost3.csv 21.55 KB	Wed, 10 Mar 2021, 10:22	xgboost with min = 20 (and not neg values or 0)	0.89767413
	solution_randomforest.csv 22.17 KB	Wed, 10 Mar 2021, 11:20	randomforest, all columns, min=20	0.89658541
	solution_lasso.csv 22.26 KB	Wed, 10 Mar 2021, 13:09	simple lasso without optimisation of the parameters, all columns, min=20	0.89791767
	solution_lasso4.csv 22.3 KB	Tue, 16 Mar 2021, 09:01	lasso, data scaled, opti, min=20	0.8989735
	solution_lgbm.csv 22.32 KB	Tue, 16 Mar 2021, 10:33	lgbm, sans opti, sans traitement, min=20	0.8961885

	solution_lasso4.csv 22.3 KB	Tue, 16 Mar 2021, 09:01	lasso, data scaled, opti, min=20	0.8989735
	solution_lgbm.csv 22.32 KB	Tue, 16 Mar 2021, 10:33	lgbm, sans opti, sans traitement, min=20	0.8961885
	solution_lgbm2.csv 22.29 KB	Tue, 16 Mar 2021, 10:41	with data scaling	0.89715968
	solution_mix.csv 22.37 KB	Tue, 16 Mar 2021, 13:12	mix xgboost3 and lasso4	0.89990392
	solution_mix2.csv 22.37 KB	Tue, 16 Mar 2021, 13:43		0.89952991
	solution_mix3.csv 22.34 KB	Wed, 17 Mar 2021, 10:43		0.89978791
	solution_mix4.csv 22.32 KB	Wed, 17 Mar 2021, 10:50		0.89955147

Conclusion

- Essayer d’autres types de pré propressing afin de trouver la manière optimale de traitement de ce type de données
- Explorer d’autres méthodes de réduction de dimension afin de garder les meilleures variables possibles
- Tester d’autres modèles de la même logique que CatBoost
- Explorer davantage le gridSearch