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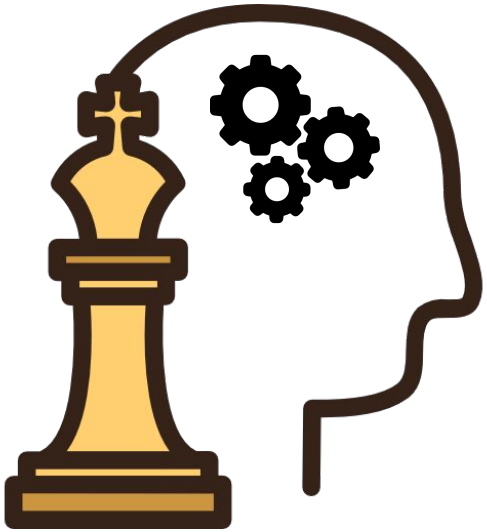

# Chess Mining

*Applying* ***KDD*** *on chess games*

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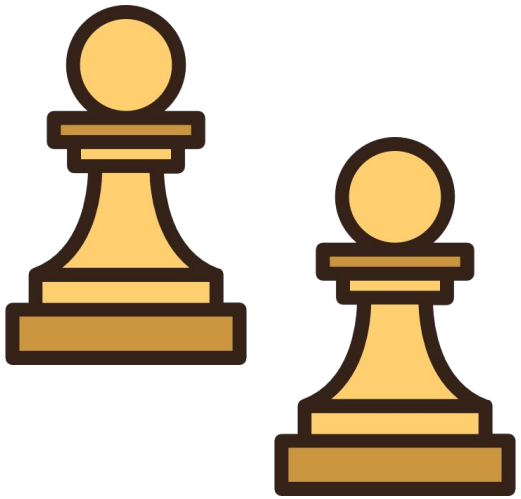
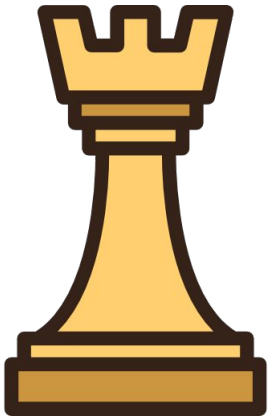


# 1. Introducción

- *DeepBlue* (fuerza bruta)
- *AlphaZero* (red neuronal profunda y aprendizaje por refuerzo)
- *Stockfish*



**Diferentes fines:**

- Jugar contra humanos
- Jugar contra otras máquinas
- Predecir resultados
- Analizar partidas

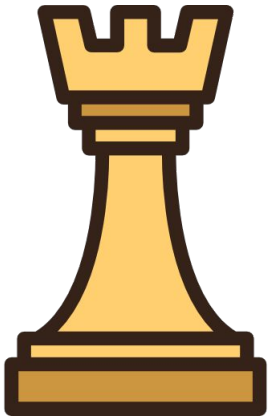
# 1. Introducción

## HIPÓTESIS

**H1** Es posible pronosticar el **resultado de un torneo**

**H2** Es posible definir los **factores de éxito** que influyen en el devenir de una partida

**H3** Es posible definir el **estilo de juego de un jugador**



## OBJETIVOS

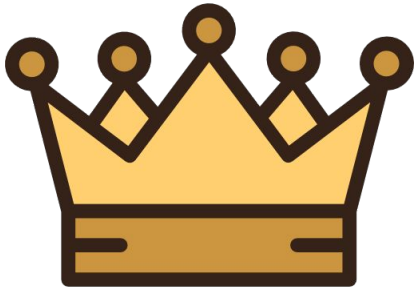
**O1** Establecer un **perfil de juego a cada jugador** en base a sus partidas

**O2** Pronosticar el **resultado de diferentes partidas individuales**

## 2. Obtención de los datos

*lichess.org*

Septiembre 2019



4.395 partidas

36.996.010 partidas

Top 200 jugadores

# 2. Obtención de los datos

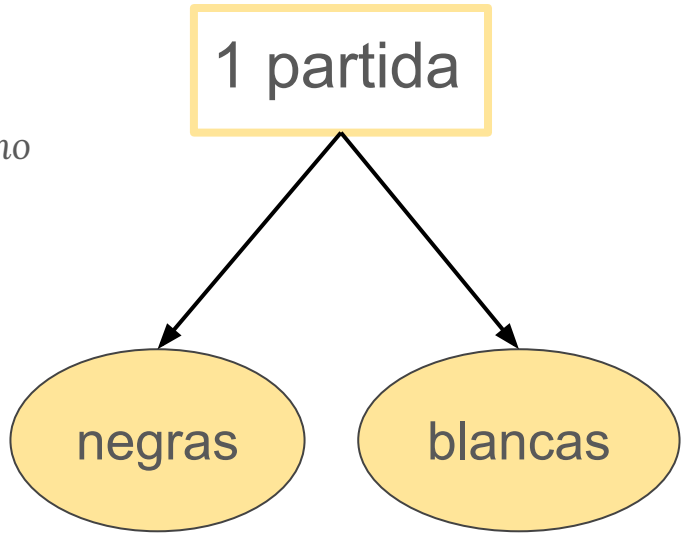
## LIBRERÍAS UTILIZADAS

- API **`berserk`**
  - Obtención de la tabla de clasificación:
    - Partidas Clásicas
    - 200 mejores jugadores
  - Obtención de las partidas:
    - Anteriores jugadores
    - Septiembre 2019
- PGN (Portable Game Notation)
- **`Python-chess`**
  - Lectura del archivo PGN con las partidas
- **`json`**, **`datetime`**, **`numpy`**

# 3. Recopilación de datos objetivo

## DATOS OBJETIVO

1. *ELO*
2. *Color*
3. *Apertura*
4. *Movimientos*
5. Tiempo:
   a. *Tiempo total*
   b. *Tiempo por jugador*
   c. *Early, middle, end → Media, mediana, varianza, máximo y mínimo*
6. *Balance de puntos*
7. *Balance de piezas*
8. Agresividad:
   a. Piezas eliminadas → Early game
   b. Apertura agresiva
   c. Castling
9. *Result* ← **variable objetivo**



# 3. Recopilación de datos objetivo

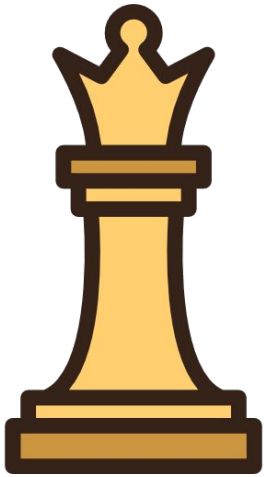
| | |
|---|---|
| **elo** | int64 |
| **colour** | category |
| **opening** | category |
| **result** | int64 |
| **movements** | int64 |
| **total_time_player** | float64 |
| **total_time** | float64 |
| **early_times_mean** | float64 |
| **early_times_median** | float64 |
| **early_times_variance** | float64 |
| **early_times_max** | float64 |
| **early_times_min** | float64 |
| **mid_times_mean** | float64 |
| **mid_times_median** | float64 |
| **mid_times_variance** | float64 |

| | |
|---|---|
| **mid_times_max** | float64 |
| **mid_times_min** | float64 |
| **end_times_mean** | float64 |
| **end_times_median** | float64 |
| **end_times_variance** | float64 |
| **end_times_max** | float64 |
| **end_times_min** | float64 |
| **points_balance** | int64 |
| **taken_balance** | int64 |
| **aggressiveness** | float64 |
| **colour_enc** | int8 |
| **opening_enc** | int16 |

# 4. Visualización y clustering

## SELECTED FEATURES

1. *elo*
2. *opening_enc*
3. *result*
4. *movements*
5. *total_time_per_player*
6. *early_times_median*
7. *early_times_max*
8. *early_times_min*
9. *mid_times_median*
10. *mid_times_max*
11. *mid_times_min*
12. *end_times_median*
13. *end_times_max*
14. *end_times_min*
15. *points_balance*



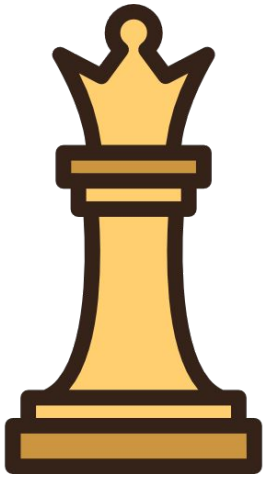
**MinMaxScaler**

# 4. Visualización y clustering

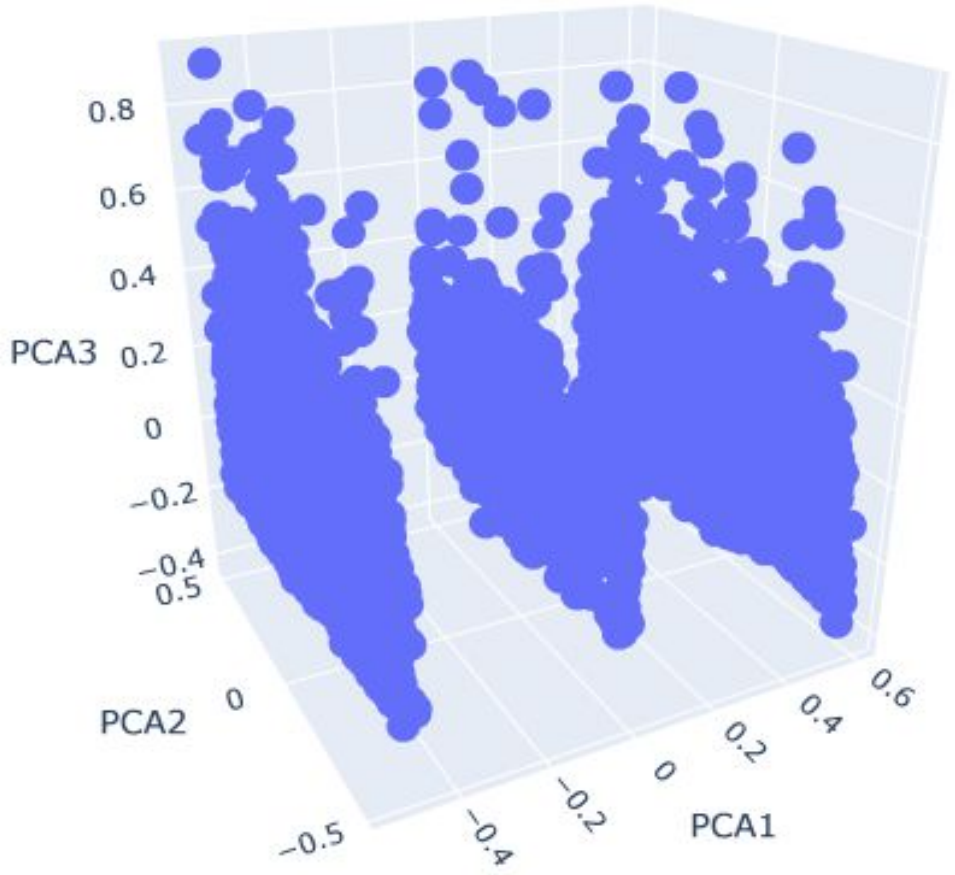
## Principal component analysis (PCA)

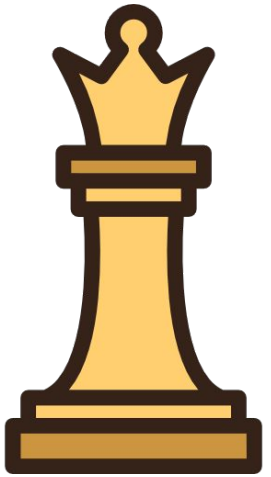
- Num. componentes = 3
  - [0.62322601, 0.22088364, 0.06225892]
  - 0.906368571968751 6 → **90%**

| | PC-0 | PC-1 | PC-2 |
|---|---|---|---|
| elo | -0.110880 | -0.006919 | 0.288907 |
| **opening_enc** | -0.000983 | **-0.999766** | 0.014340 |
| **result** | **-0.989784** | 0.001753 | -0.033313 |
| **movements** | -0.000406 | 0.000115 | **0.443249** |
| **total_time_player** | 0.001063 | 0.015091 | **0.730605** |
| early times median | -0.001556 | 0.002331 | 0.090972 |
| early times max | -0.000368 | 0.004323 | 0.229377 |
| early times min | -0.001495 | 0.000307 | 0.014759 |
| mid times median | -0.001311 | 0.011402 | 0.302232 |
| mid times max | 0.000450 | 0.003064 | 0.076533 |
| mid times min | -0.005953 | 0.004159 | 0.075692 |
| end times median | 0.001603 | 0.002938 | 0.055031 |
| end times max | 0.003802 | -0.000395 | 0.132851 |
| end times min | -0.001926 | 0.000521 | 0.010731 |
| points_balance | -0.089260 | -0.000120 | 0.011578 |



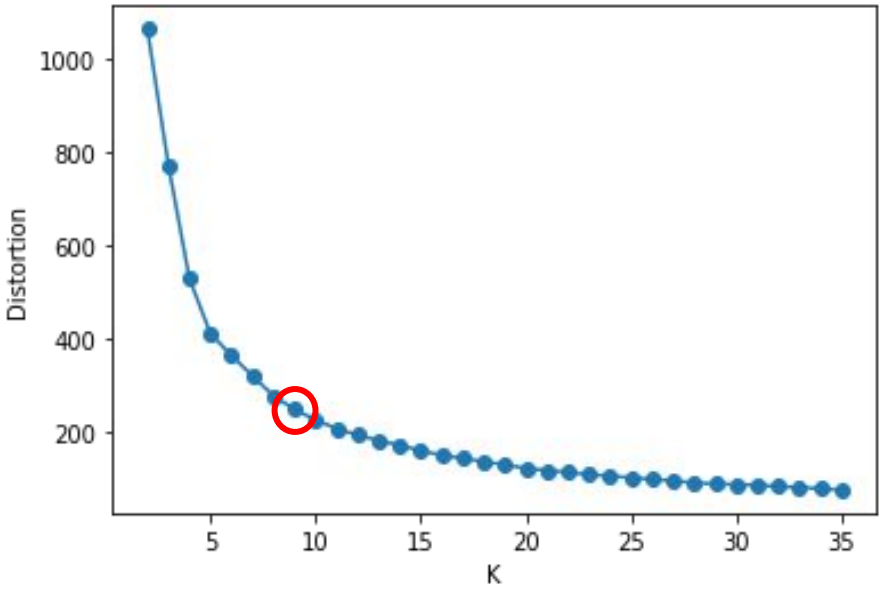
# 4. Visualización y clustering



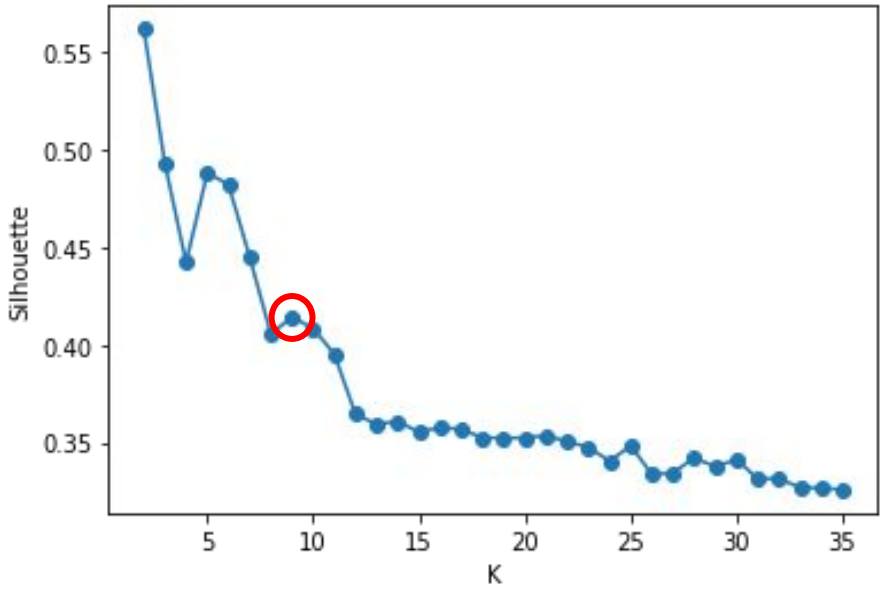



# 4. Visualización y clustering

## Distortion



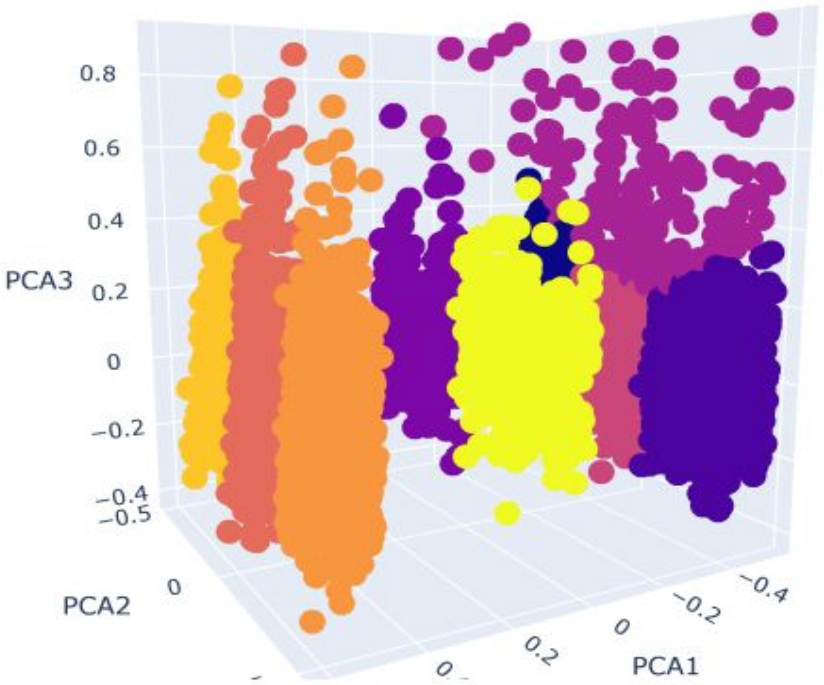

## Silhouette

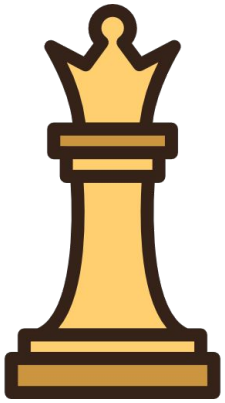


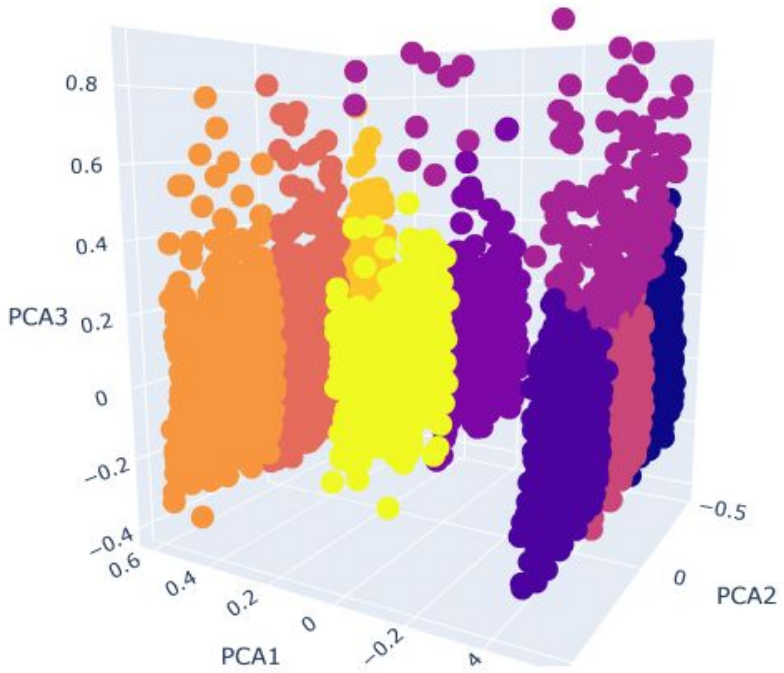

**K = 9**

**Silhouette Coefficient:** 0.414
**Distortion:** 247.02

# 4. Visualización y clustering

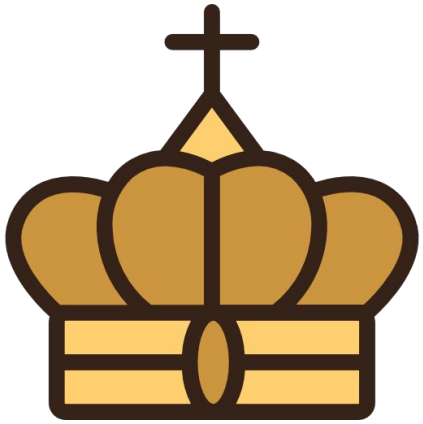




# 5. Modelo de predicción

## PROCESO



1. Carga de datos (**source**)
2. Generación del **dataset**
3. Filtrado de variables

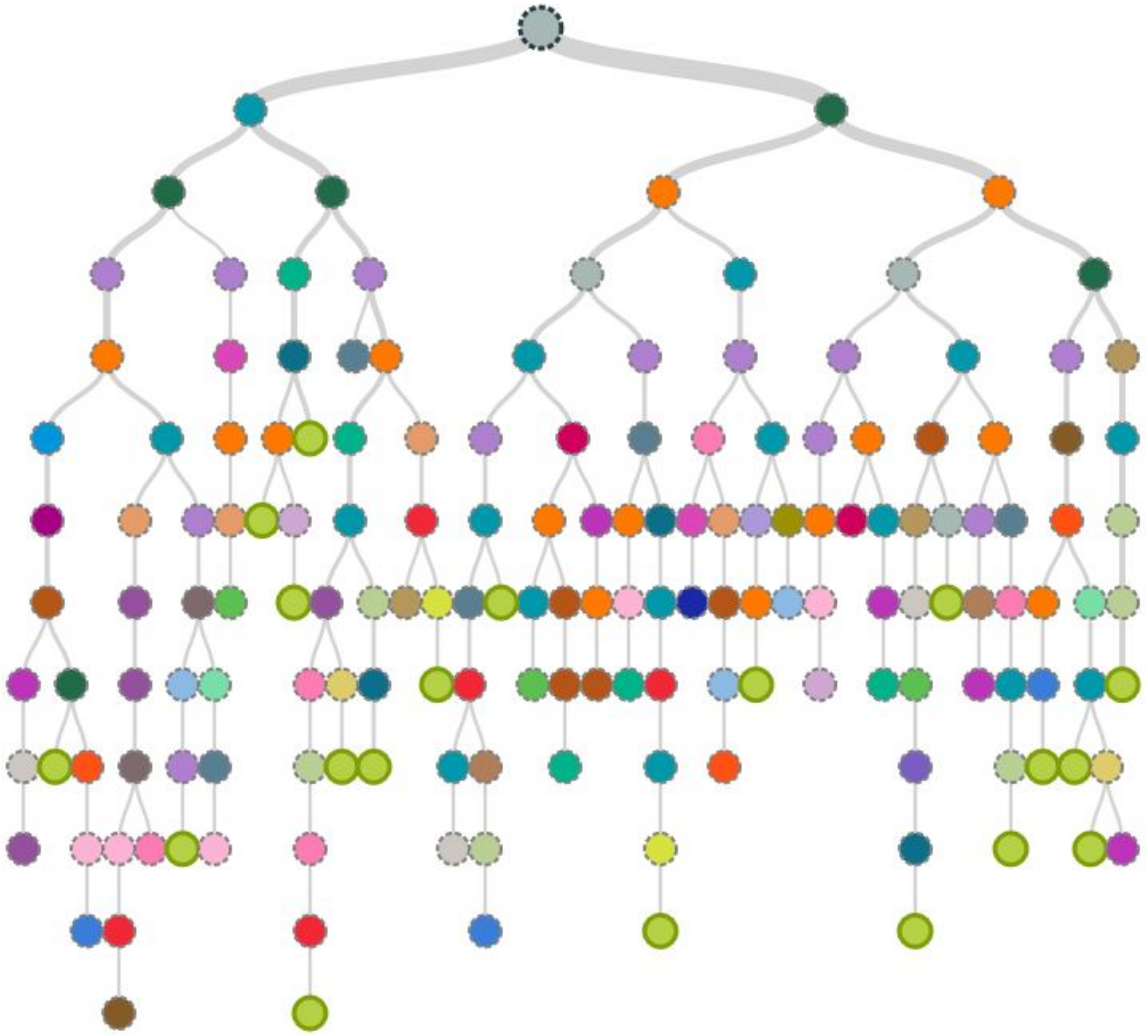
   *Descartamos IDs de los usuarios, nombre de la apertura e ID de cada uno de los registros.*

4. Construcción del **modelo**

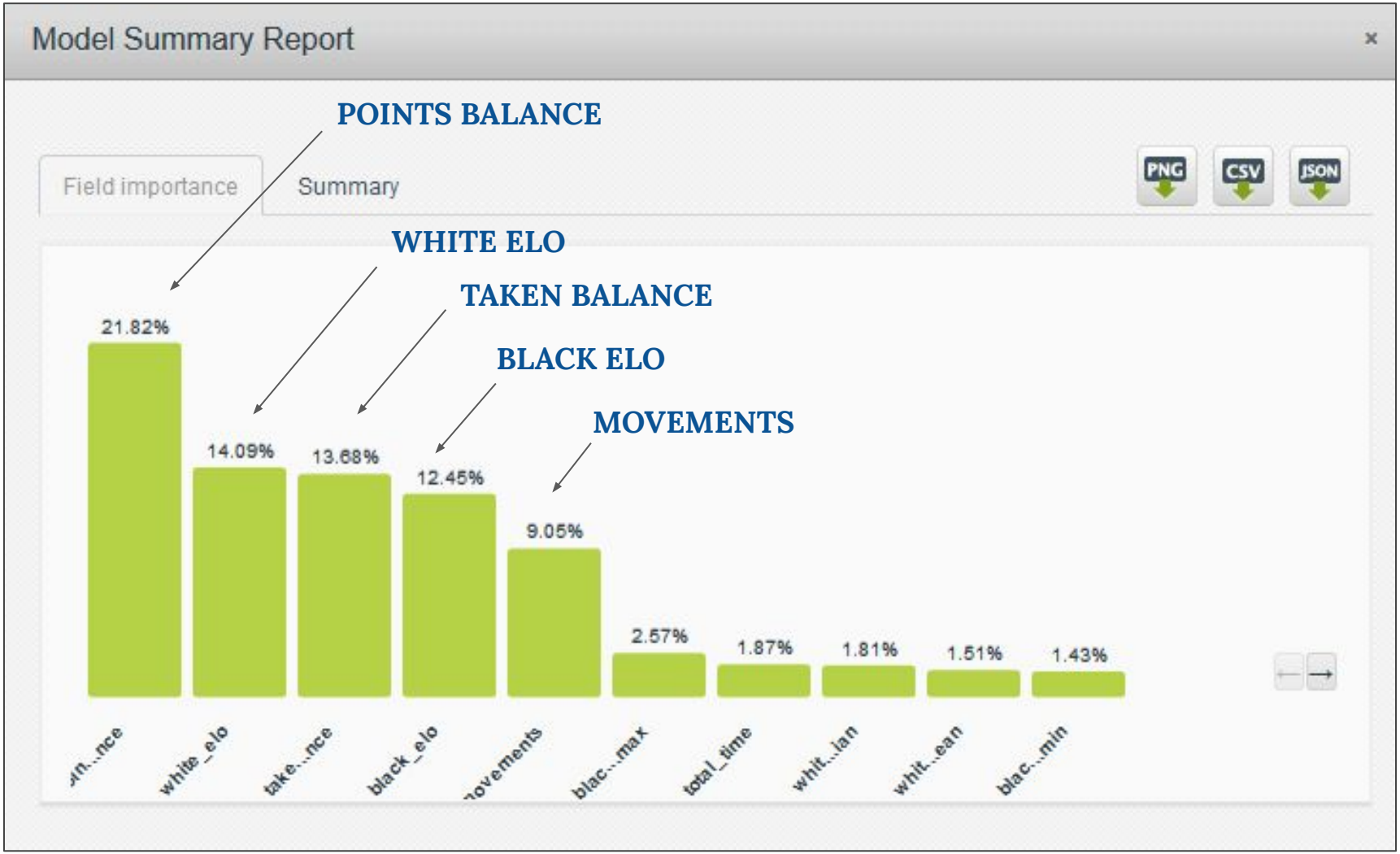
bigml®

# Generamos el modelo...

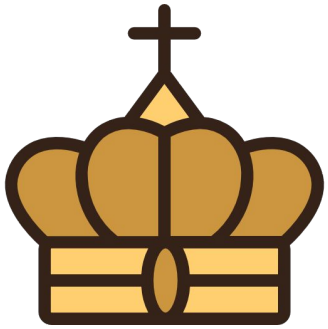
# 5. Modelo de predicción



# 5. Modelo de predicción



# 5. Modelo de predicción



*Matriz de confusión*

## GANAN BLANCAS `(result=0)`

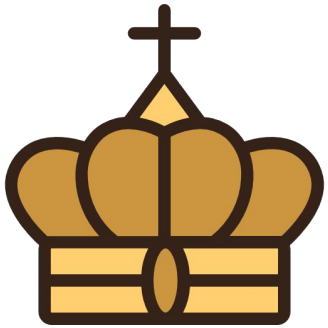
TP FN FP TN

| ACTUAL VS. PREDICTED | 0 | 1 | 2 | ACTUAL | RECALL | F | Phi |
|---|---|---|---|---|---|---|---|
| 0 | 859 | 39 | 300 | 1,198 | **71.70%** | 0.76 | 0.56 |
| 1 | 59 | 18 | 114 | 191 | **9.42%** | 0.13 | 0.10 |
| 2 | 148 | 27 | 886 | 1,061 | **83.51%** | 0.75 | 0.53 |
| PREDICTED | 1,066 | 84 | 1,300 | 2,450 | **54.88%** AVG. RECALL | **0.55** AVG. F | **0.40** AVG. Phi |
| PRECISION | **80.58%** | **21.43%** | **68.15%** | **56.72%** AVG. PRECISION | 71.96% ACCURACY | | |

| | |
|---|---|
| 77.7% Accuracy | 0.7588 F-measure |

| | | |
|---|---|---|
| 80.6% Precision | 71.7% Recall | 0.5563 Phi coefficient |

# 5. Modelo de predicción



*Matriz de confusión*

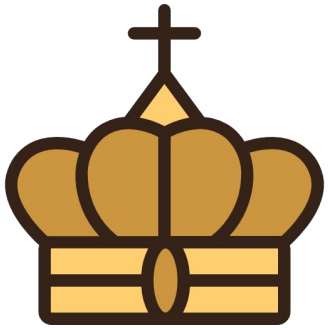
## TABLAS `(result=1)`

TP FN FP TN

| ACTUAL VS. PREDICTED | 0 | 1 | 2 | ACTUAL | RECALL | F | Phi |
|---|---|---|---|---|---|---|---|
| 0 | 859 | 39 | 300 | 1,198 | 71.70% | 0.76 | 0.56 |
| 1 | 59 | 18 | 114 | 191 | 9.42% | 0.13 | 0.10 |
| 2 | 148 | 27 | 886 | 1,061 | 83.51% | 0.75 | 0.53 |
| PREDICTED | 1,066 | 84 | 1,300 | 2,450 | 54.88% AVG. RECALL | 0.55 AVG. F | 0.40 AVG. Phi |
| PRECISION | 80.58% | 21.43% | 68.15% | 56.72% AVG. PRECISION | 71.96% ACCURACY | | |

| | | |
|---|---|---|
| 90.2% Accuracy | | 0.1309 F-measure |
| 21.4% Precision | 9.4% Recall | 0.0958 Phi coefficient |

# 5. Modelo de predicción



*Matriz de confusión*

## GANAN NEGRAS `(result=2)`

TP FN FP TN

| ACTUAL VS. PREDICTED | 0 | 1 | 2 | ACTUAL | RECALL | F | Phi |
|---|---|---|---|---|---|---|---|
| 0 | 859 | 39 | 300 | 1,198 | **71.70%** | 0.76 | 0.56 |
| 1 | 59 | 18 | 114 | 191 | **9.42%** | 0.13 | 0.10 |
| 2 | 148 | 27 | 886 | 1,061 | **83.51%** | 0.75 | 0.53 |
| PREDICTED | 1,066 | 84 | 1,300 | 2,450 | **54.88%** AVG. RECALL | **0.55** AVG. F | **0.40** AVG. Phi |
| PRECISION | **80.58%** | **21.43%** | **68.15%** | **56.72%** AVG. PRECISION | 71.96% ACCURACY | | |

| | |
|---|---|
| 76.0% Accuracy | 0.7505 F-measure |

| | | |
|---|---|---|
| 68.2% Precision | 83.5% Recall | 0.5332 Phi coefficient |

# 7. Resultados obtenidos

**H1** Es posible pronosticar el **resultado de un torneo**

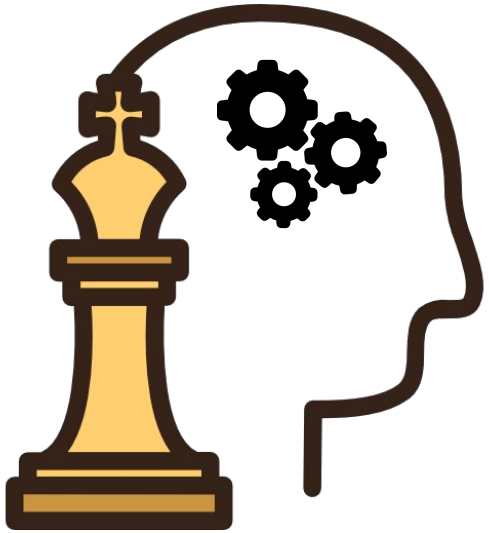
- ➢ **Pronóstico de partidas mediante el modelo**
- ➢ **Alta precisión**

**H2** Es posible definir los **factores de éxito** que influyen en el devenir de una partida

- ➢ **Variables más influyentes en el modelo**

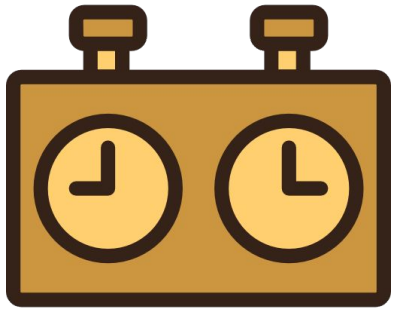
**H3** Es posible definir el **estilo de juego de un jugador**

- ➢ **Clustering → perfiles de los jugadores**



# 7. Trabajo futuro

- Un modelo que no requiera del balance de **piezas comidas** / **puntos** para llevar a cabo la predicción.



*Aunque...*

- El ajedrez no es similar a otros juegos competitivos donde acumular más puntos siempre significa ganar.
  - **Especialmente en niveles profesionales**.

- ¿Búsqueda de otros posibles factores de predicción?

# ¡A jugar!