



Data Barbarians: PCA-driven User Engagement Measurement

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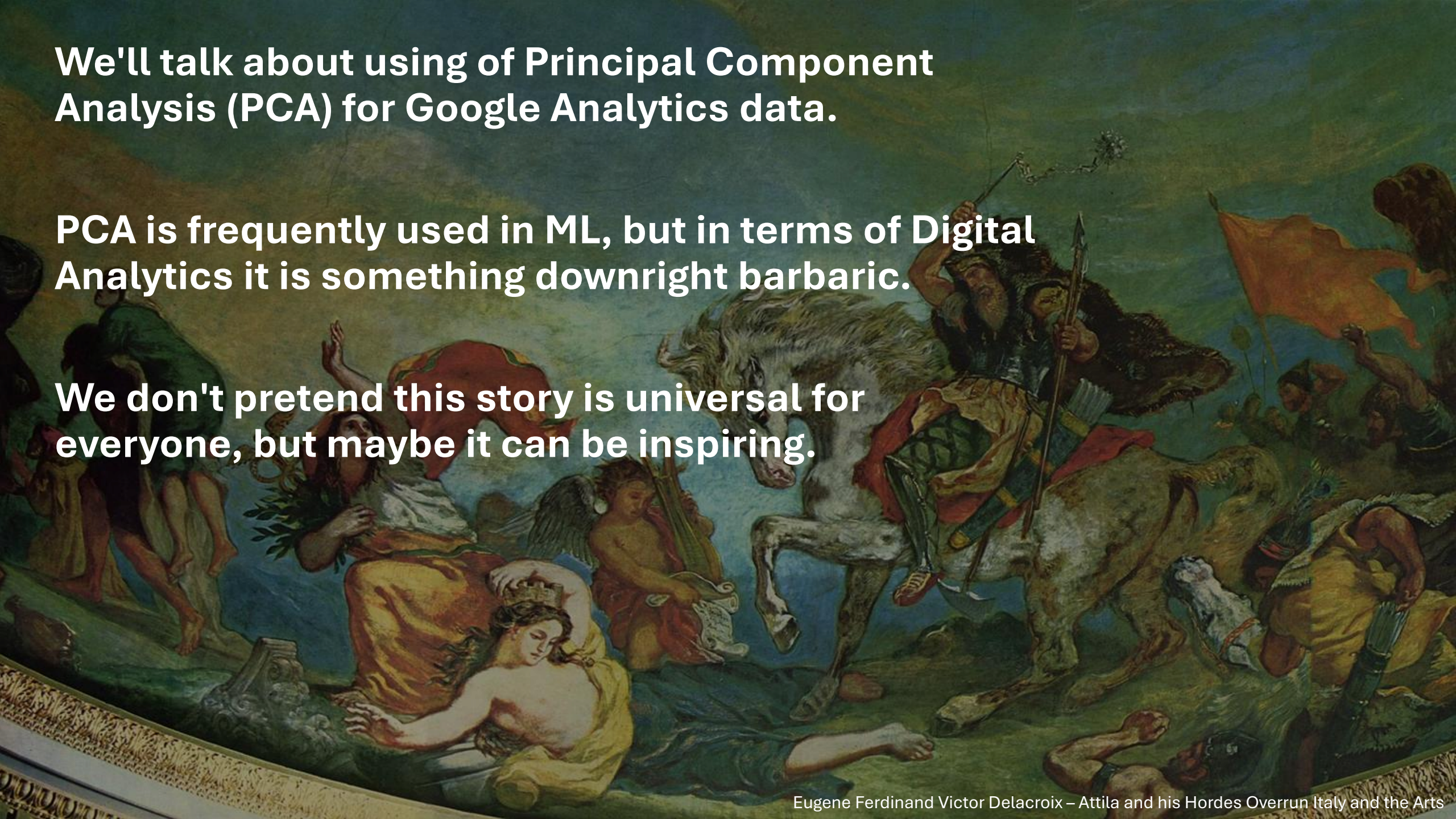
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We'll talk about using of Principal Component Analysis (PCA) for Google Analytics data.

PCA is frequently used in ML, but in terms of Digital Analytics it is something downright barbaric.

We don't pretend this story is universal for everyone, but maybe it can be inspiring.



Eugene Ferdinand Victor Delacroix – Attila and his Hordes Overrun Italy and the Arts

Let's start!



Thomas Cole – The Course of Empire: The Consummation of Empire

Let's imagine that we have a media portal!

Portal

Articles Section

Quizzes Section

**User Content
Section**

**Special Projects &
Games Section**

Each section has its own development team, core audience and engagement metrics

Portal:

- Website-level Metrics 1
- Website-level Metrics 2
- Website-level Metrics 3

Articles Section

- Metrics 1
- Metrics 2
- Metrics 3

Quizzes Section

- Metrics 1
- Metrics 2
- Metrics 3

User Content Section

- Metrics 1
- Metrics 2
- Metrics 3

Special Projects & Games Section

- Metrics 1
- Metrics 2
- Metrics 3



How can we measure user engagement?

**Let's use basic GA4-
driven engagement
metrics**

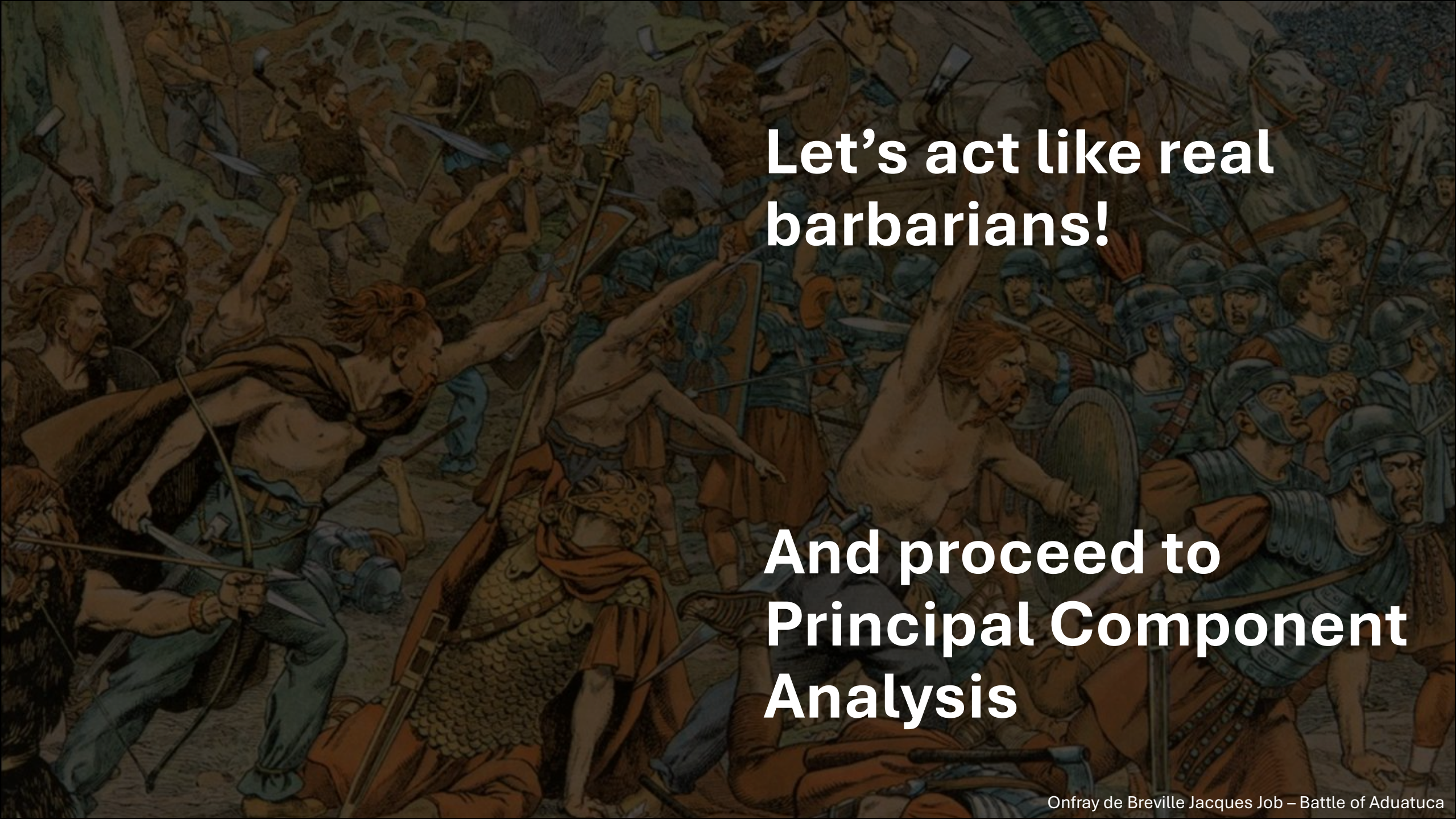
**Let's rely on
website-level
metrics**

**Let's rely on
section-specific
metrics**

*Sometimes it is too
generic/non-
indicative*

*It cannot say how
separate sections
perform*

*It doesn't show a full
picture*

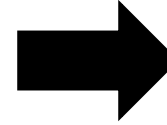


**Let's act like real
barbarians!**

**And proceed to
Principal Component
Analysis**

Principal Component Analysis is (almost) your personal data archiver

user_id	metrics1	metrics2	metrics3	...	metrics100
0	100	27	45	...	50
1	86	17	45	...	4
2	94	21	40	...	56
3	83	29	44	...	62
4	87	18	43	...	48
5	82	11	47	...	7
6	97	23	47	...	61



user_id	pc1	pc2
0	-0.13	-1.14
1	-0.55	0.03
2	-0.15	-1.22
3	1.66	-0.29
4	0.74	-0.68
5	-0.64	1.32
6	0.51	0.12

- PCA transforms selected metrics to abstract dimensions/indexes
- In terms of digital analytics, principal components can be used in:
 - metrics patterns reveal
 - user segmentation
 - building of abstract-level metrics

We already can do it!

- BigQuery ML
- Google Colab
(pandas/numpy + scikit learn)
- R
- IBM SPSS
- A lot of other variants!



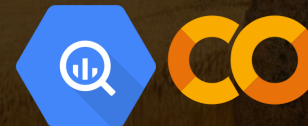
1. Data Collection

User behavior tracking handled by GTM + GA4

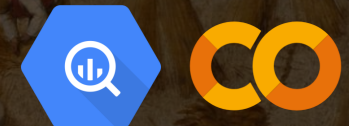


3. Data cleaning & standardize

Outliers exclusion & transformation of metrics to the same scale



5. Results validation & evaluation



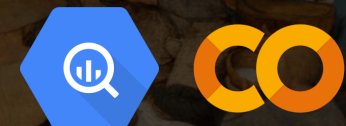
2. Data Preparation/Transformation

Transforming of raw data to actionable tables in BigQuery



4. PCA Model Initialize

Definition of number of principal components



Data Preparation

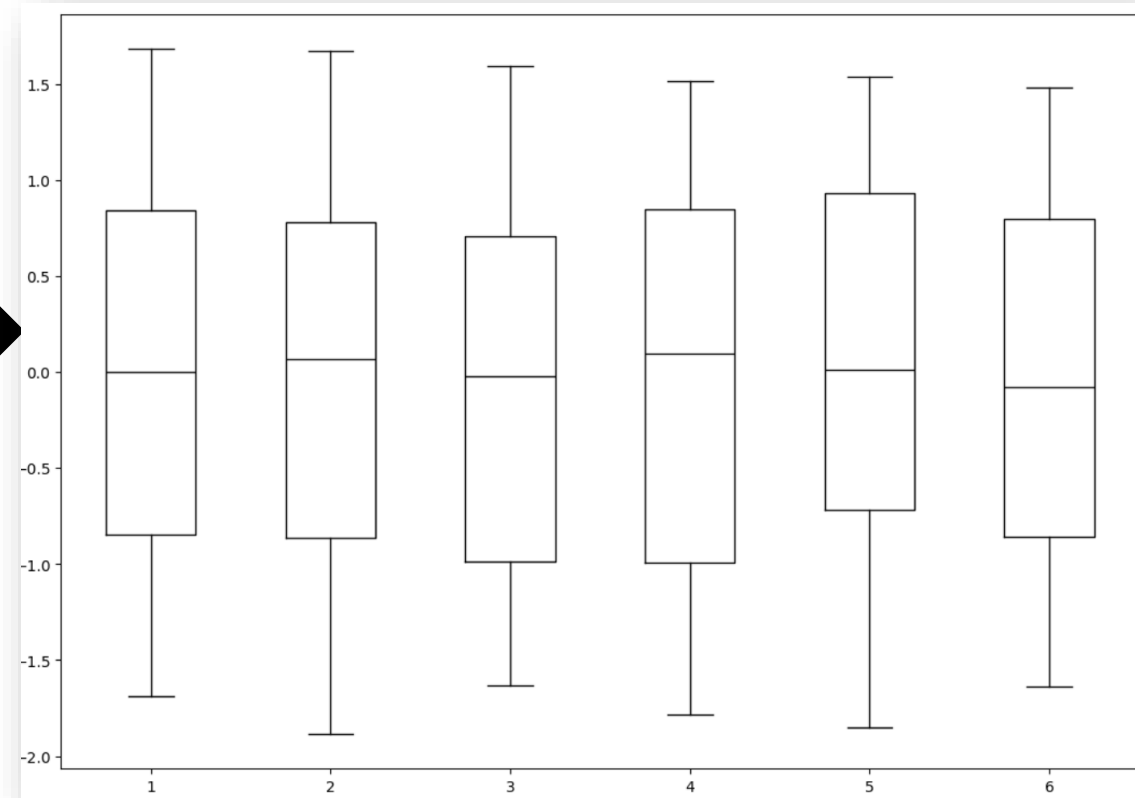
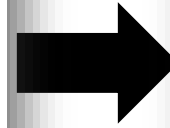
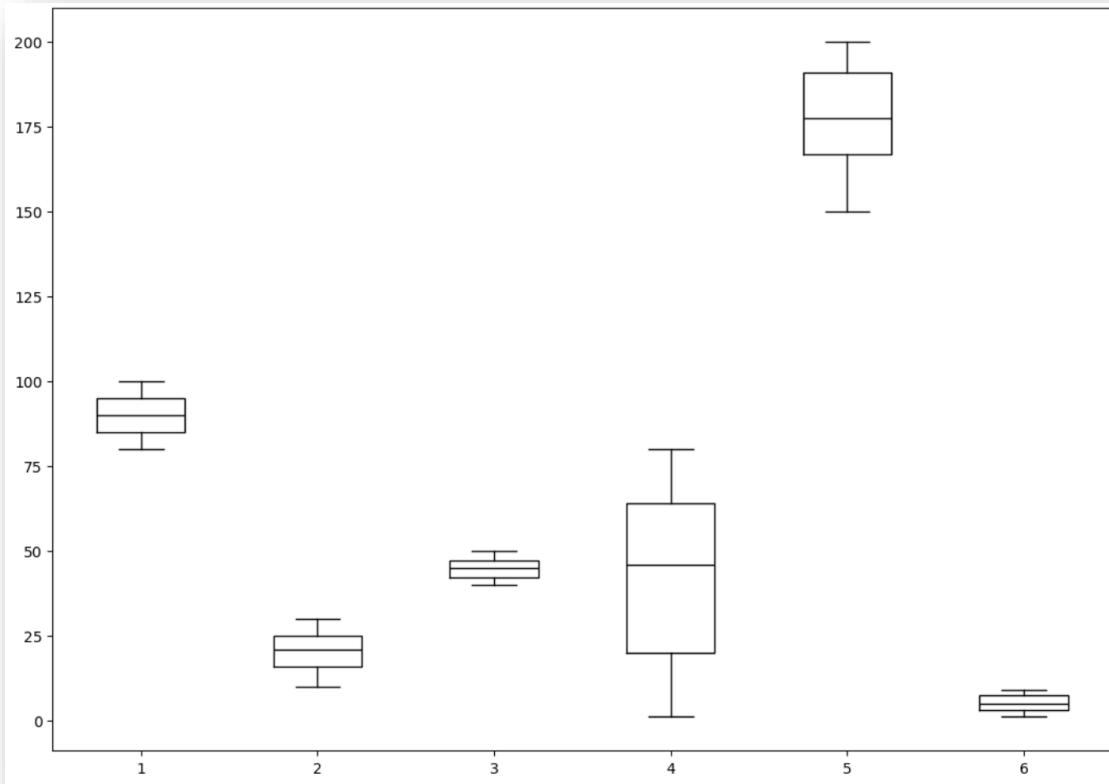
Making of session-based or user-based tables with engagement metrics as columns

Limitations:

- It is applicable only for numerical or ordinal variables
- It is not so effective in non-linear cases – in that case better use kPCA or other DR methods

```
CREATE OR REPLACE TABLE `project.dataset.session_features` AS
WITH agg AS (
  SELECT
    session_id,
    SUM(CASE WHEN event_name = 'metrics1' THEN 1 ELSE 0 END) AS metrics1,
    SUM(CASE WHEN event_name = 'metrics2' THEN 1 ELSE 0 END) AS metrics2,
    SUM(CASE WHEN event_name = 'metrics3' THEN 1 ELSE 0 END) AS metrics3,
    SUM(CASE WHEN event_name = 'metrics4' THEN 1 ELSE 0 END) AS metrics4,
    SUM(CASE WHEN event_name = 'metrics5' THEN 1 ELSE 0 END) AS metrics5,
    SUM(CASE WHEN event_name = 'metrics6' THEN 1 ELSE 0 END) AS metrics6,
  FROM base
  GROUP BY session_id
)
SELECT * FROM agg;
```


Data cleaning & standardize



Can be done with:

- Built-in BigQuery ML or Scikit-learn options
- Z-score normalization
- Exclusion of outliers (99th or 95th percentile)
- Log1p approach

PCA Model Initialization

In BigQuery ML, we can either select number of components or define target explained variance

```
CREATE OR REPLACE MODEL `project.dataset.pca_user_behavior`  
OPTIONS (  
  model_type = 'pca',  
  num_principal_components = 2  
) AS  
SELECT  
  z_metrics1, z_metrics2, z_metrics3, z_metrics4, z_metrics5, z_metrics6  
FROM `project.dataset.session_features_z`;
```


Checking results

Top things to check:

- Explained variance (bigger is better)
- Pivot between principal components and initial metrics

Limitation: In case our web product changes significantly over time, we need to re-train our PCA model

Metrics

Total explained variance ratio	0.8546
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principal_compo...	eigenvalue ▼	explained_varian...	cumulative_expla...
0	3.465726082270...	0.577621013711...	0.577621013711...
1	0.976709321654...	0.162784886942...	0.740405900654...

feature	pc1	pc2
z_metrics1	0.52	-0.07
z_metrics2	0.35	0.10
z_metrics3	0.49	-0.06
z_metrics4	0.49	-0.02
z_metrics5	0.13	0.96
z_metrics6	0.33	-0.25

What can we do with that next?



Fra Carnevale – The Ideal City



Gentile Bellini – Procession in St. Mark's Square



Nicolas Bertin – Hercules fighting Achelous

A path of wisdom

Source: <https://dl.acm.org/doi/10.1145/3341981.3344222>

Metrics patterns definition

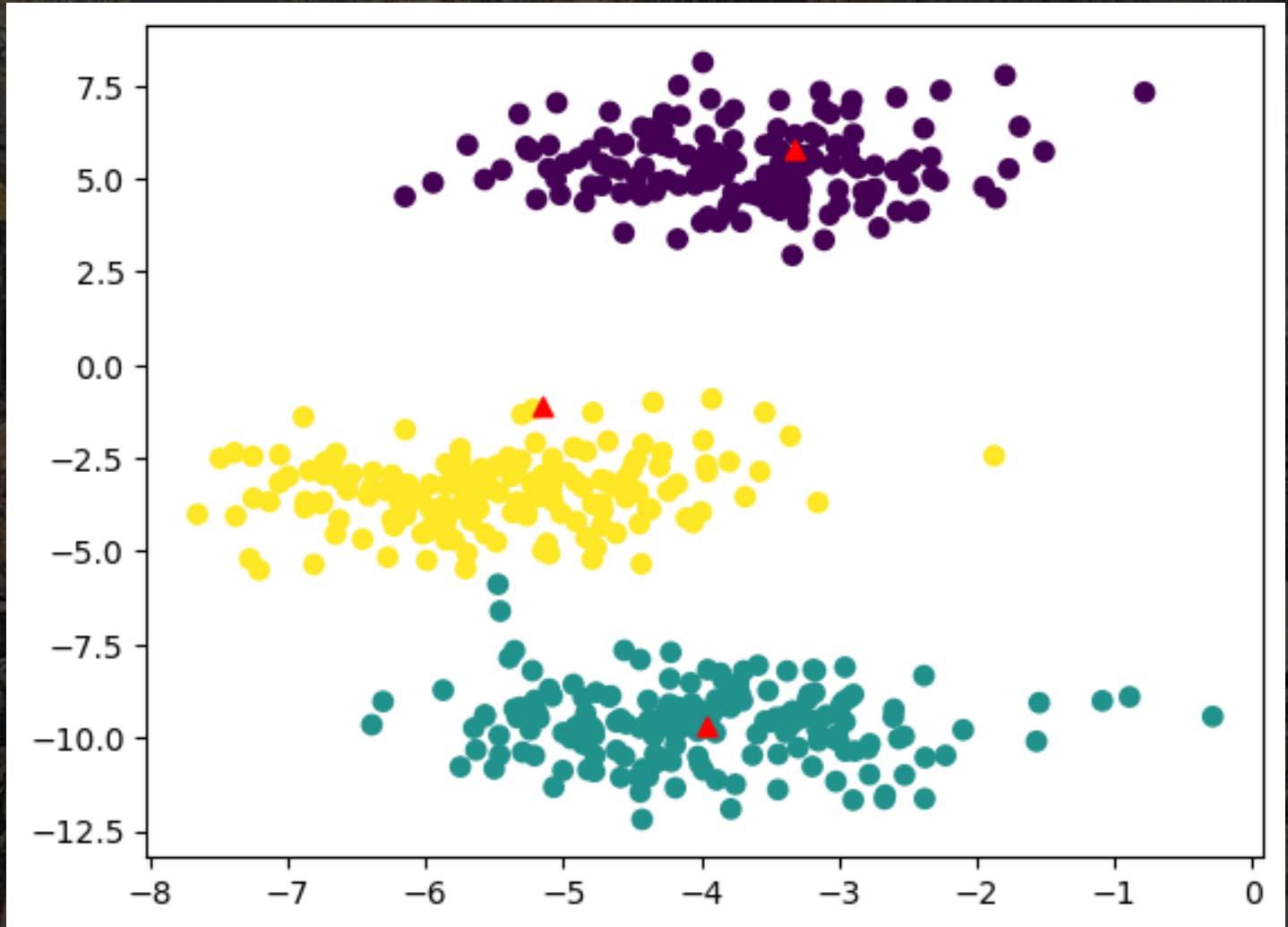
Checking metrics
numeric values +
grouping them by
principal
components

	PC1 (AbandQs)	PC2 (AbandCs)	PC3 (DeepSERP)	PC4 (Pace)	PC5 (NLQs)	PC6 (SlowCs)
QueriesWOBooks	0.87	0.09	0.27	0.04	0.06	-0.03
QueriesWOClicks	0.86	-0.03	0.21	0.21	-0.04	0.02
Queries	0.85	0.16	0.10	-0.29	0.15	0.04
RepeatedIntentQs	0.85	0.14	0.24	-0.02	0.02	0.12
QuickReforms	0.83	0.00	0.09	-0.18	-0.20	-0.05
UniqueQueries	0.82	0.15	0.09	-0.16	0.37	0.00
QueriesWOMouse	0.71	0.02	-0.08	0.15	-0.16	-0.09
UniqueQueryTerms	0.62	0.04	-0.05	0.04	0.36	0.30
QueriesWOScrolls	0.60	0.16	-0.44	-0.33	-0.03	-0.04
Clicks	0.16	0.83	0.22	-0.37	0.07	-0.18
ClicksWOBooks	0.18	0.79	0.25	0.13	0.02	-0.24
UniqueURLs	0.04	0.76	0.08	-0.05	0.12	0.09
CompletionTime	0.05	0.57	0.08	0.53	0.08	0.34
MouseWOClicks	0.34	0.18	0.85	-0.11	0.14	0.06
Mouseovers	0.16	0.40	0.82	-0.09	0.07	-0.02
Paginations	-0.09	0.18	0.78	0.01	-0.09	0.10
ScrollDistance	0.36	-0.06	0.77	-0.03	0.22	0.12
AvgTimeBWEvents	-0.26	-0.05	-0.07	0.83	-0.03	0.31
Bookmarks	-0.02	0.27	-0.07	-0.78	-0.01	0.09
TimeToFirstBook	0.06	0.19	-0.17	0.70	-0.12	0.22
QuestionQueries	0.02	0.08	0.13	0.01	0.83	-0.08
AvgQueryLength	0.01	0.10	0.03	-0.09	0.82	0.10
TimeToFirstClick	0.04	-0.02	0.02	0.12	0.06	0.82
Avg1stClickTime	0.05	-0.13	0.34	0.30	-0.04	0.70

A path of might

Segmentation based on principal components

Saving of principal component values in a separate table + application of k-means clustering



A path of courage – I totally would not recommend it!

Website Section 1
Dataset



Website Section 2
Dataset

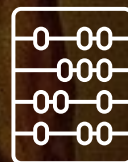


Website Section 3
Dataset



PCA Level 1

Website Section 1
Principal Component



Website Section 2
Principal Component

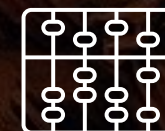


Website Section 3
Principal Component



PCA Level 2

Website-level
Principal Component
(e.g. Engagement index)



Summary



Why is it good to try PCA?

- It is another good entry point to start working with applied statistics!
- It can help to uncover additional patterns to user engagement understanding
- Findings of PCA then can be used in terms of propensity modelling
- **We need to do something barbaric before transition to Ancient Greeks of Digital Analysis**



Raphael – School of Athens

Let's connect!

- GitHub with scripts:
https://github.com/Lunthu/ga4_pca
- LinkedIn: <https://www.linkedin.com/in/victor-laputsky-44199bab/>

