Meet Your Customers

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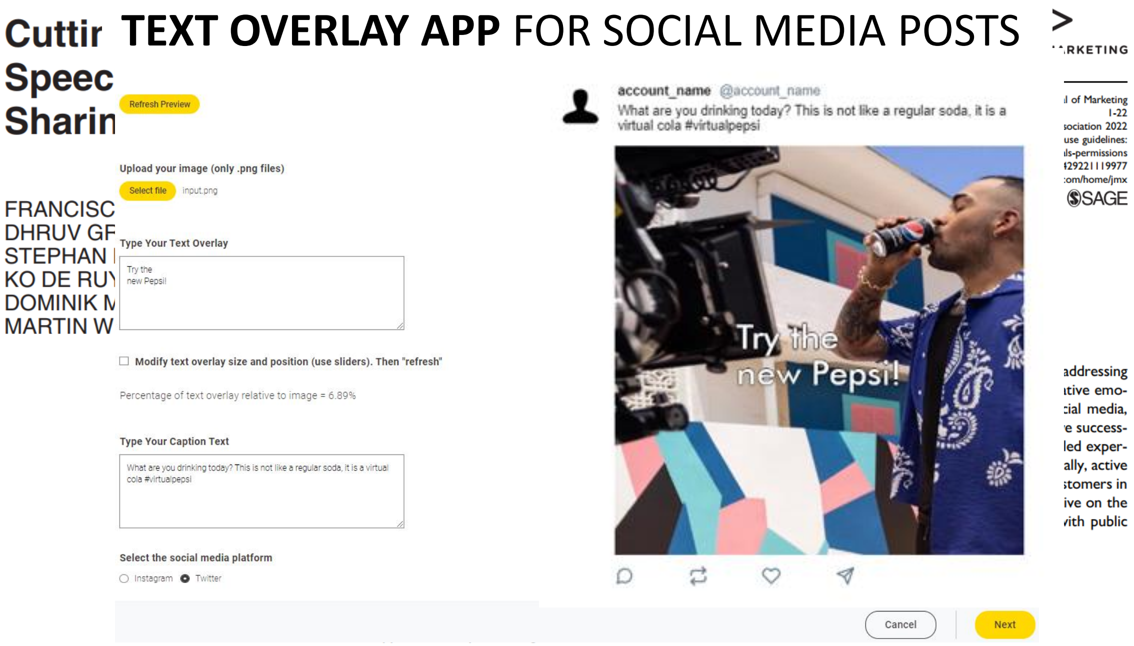
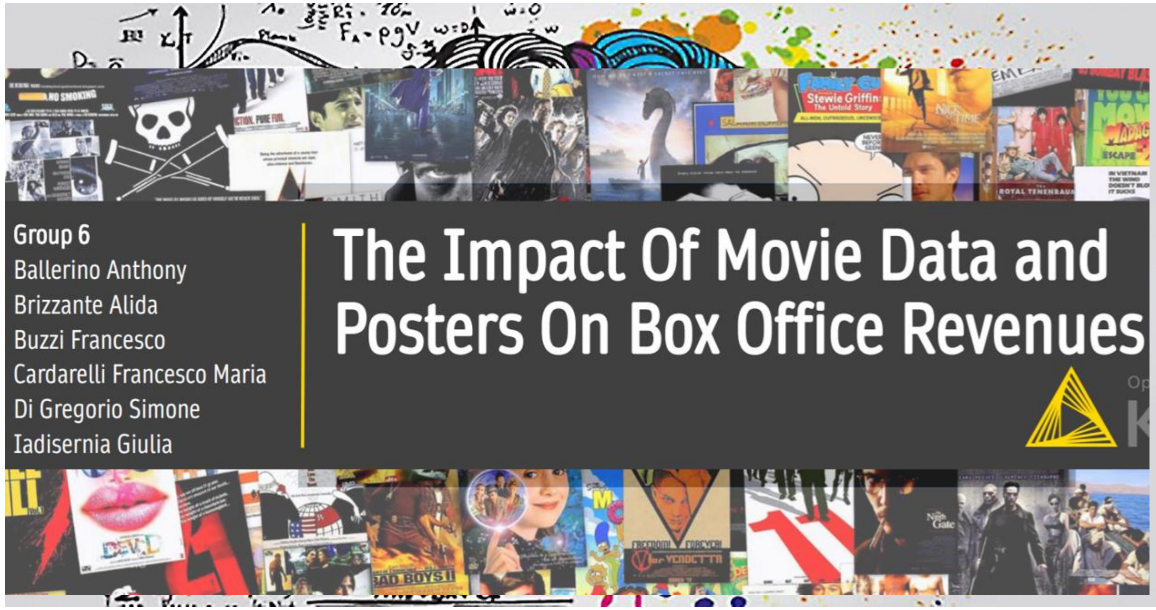
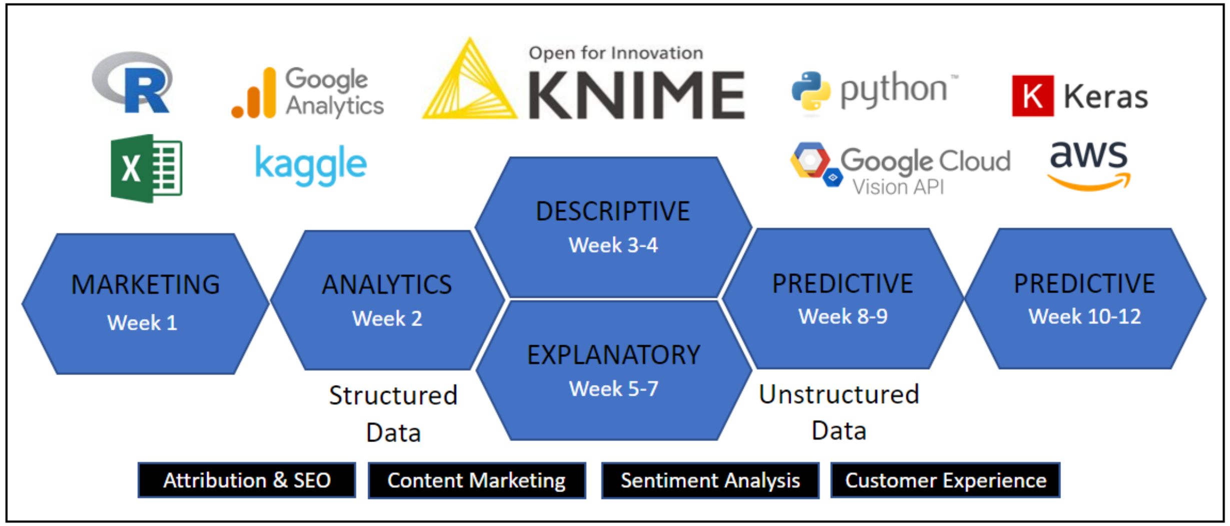




Creative Industries Challenge 2020



BUSINESS & MARKETING ANALYTICS FRAMEWORK

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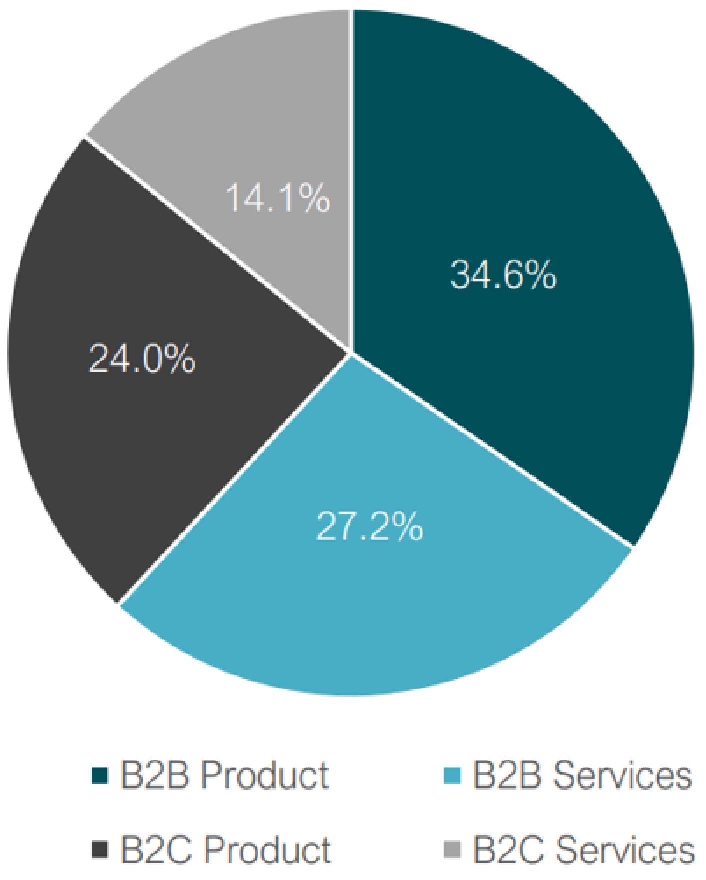
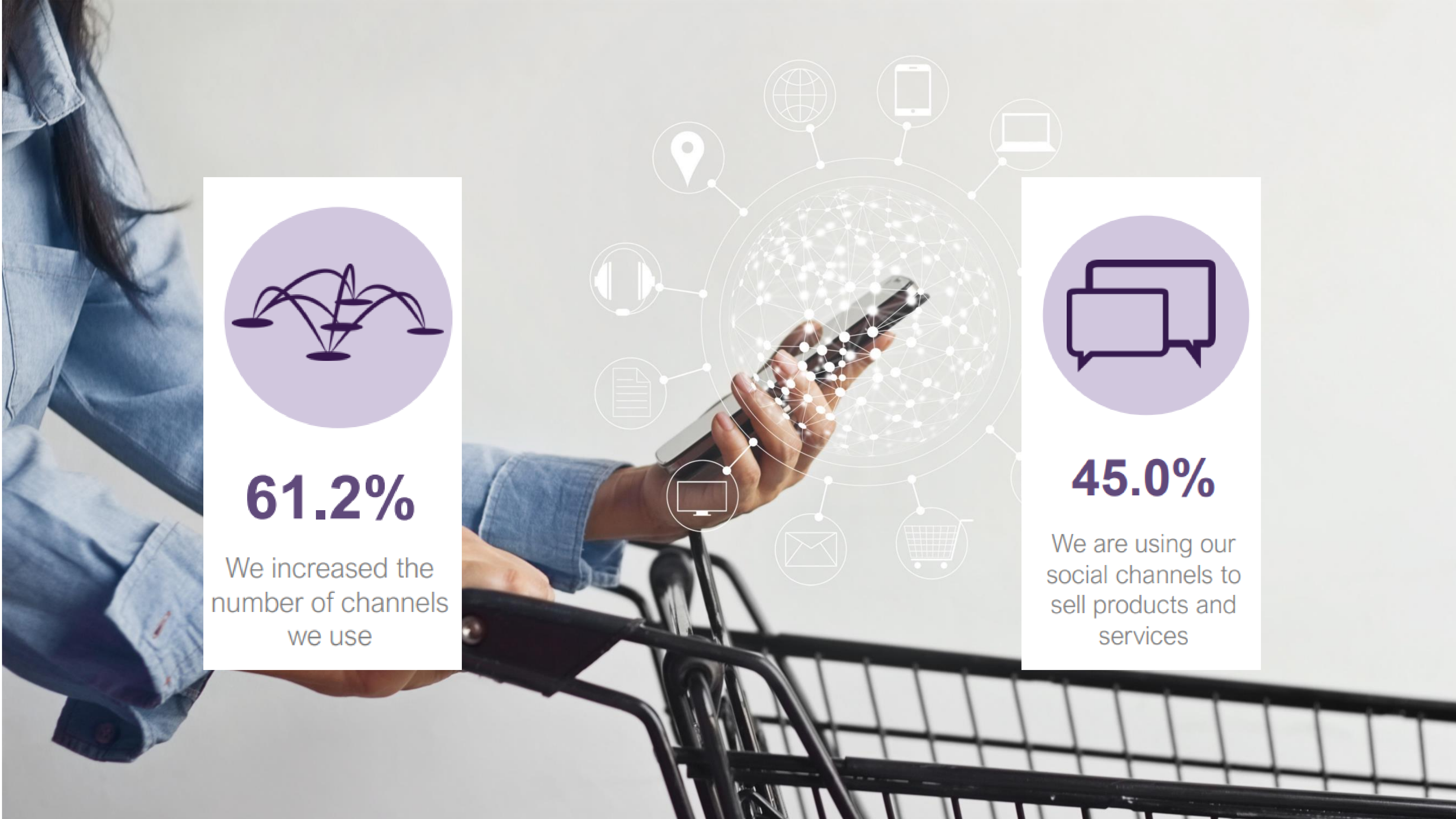
The CMO Survey®

- Sample of 2,747 Marketing Leaders among top for-profit companies

- Results from March 2023 – 314 respondents (97% of respondents with at VP level or above)

ECONOMIC SECTOR




61.2%
We increased the number of channels we use
45.0%
We are using our social channels to sell products and services

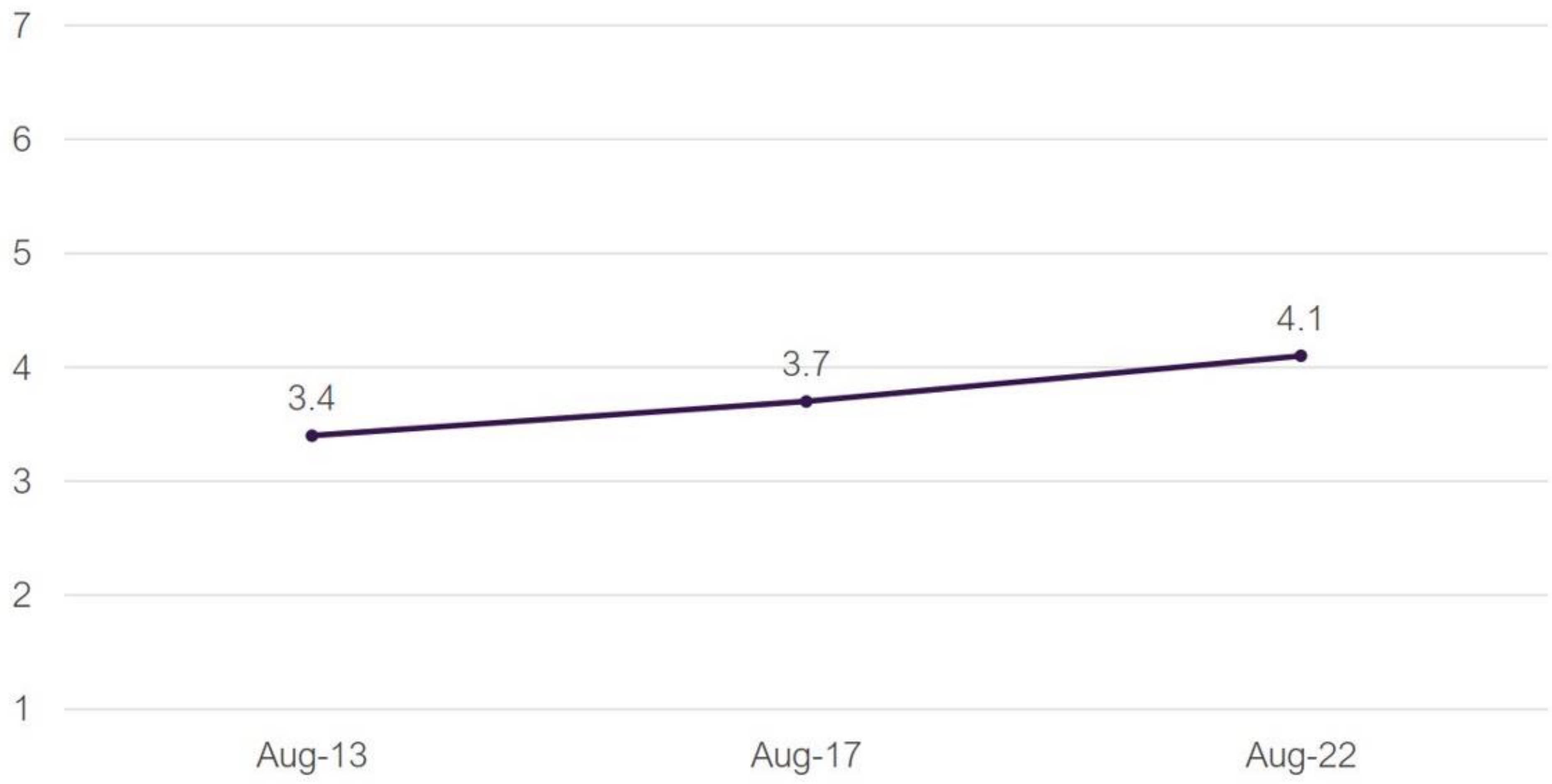
What is Marketing primarily responsible in your company?

Activity	March 2023	Increase from 2020
Brand	94.1%	↑4.1%
Advertising	92.3%	↑6.3%
Digital Marketing	90.5%	↑4.5%
Social Media	80.6%	↓0.1%
Marketing Analytics	77.9%	**↑11.3%**
Marketing Research	73.9%	**↑13.2%**
Insight	56.8%	↑3.5%
Competitive Intelligence	55.9%	↑8.6%

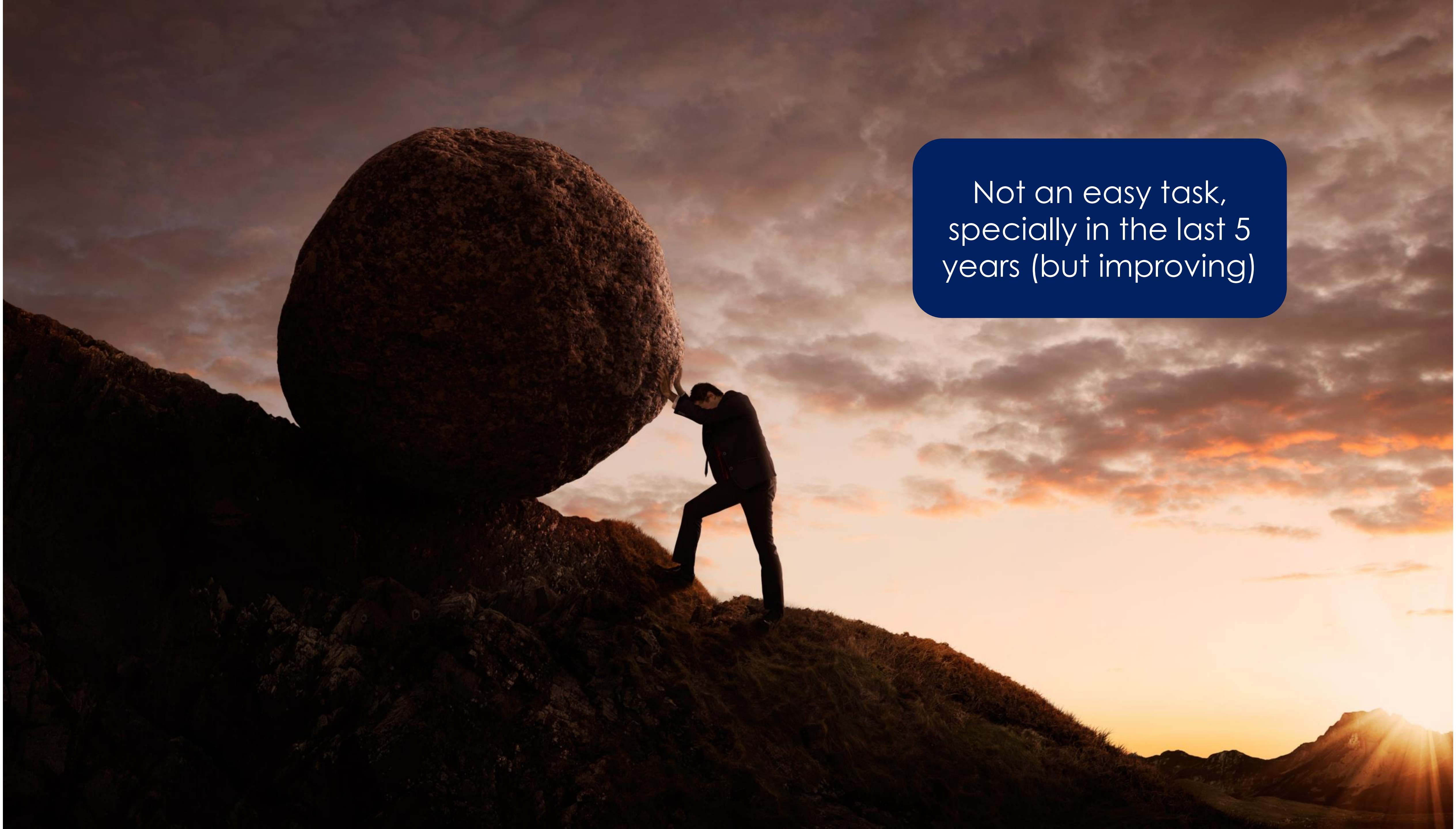
Marketing professionals need to know how **ADD VALUE** to product and service offerings

Marketing professionals need to know how **MEASURE VALUE CREATION** through marketing activities

To what extent does your company have the right talent to fully leverage marketing analytics? (1= Does not have the right talent; 7= Has the right talent)



There is a difficult to fill **professional GAP.** It requires abilities in marketing research, data scraping, statistics, machine learning, and (potentially) app building


Not an easy task,
specially in the last 5
years (but improving)

“Meet your Customers”

Result of 3 years of collaboration with the evangelist team

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Machine learning for marketing on the KNIME Hub: The deve
live repository for marketing applications

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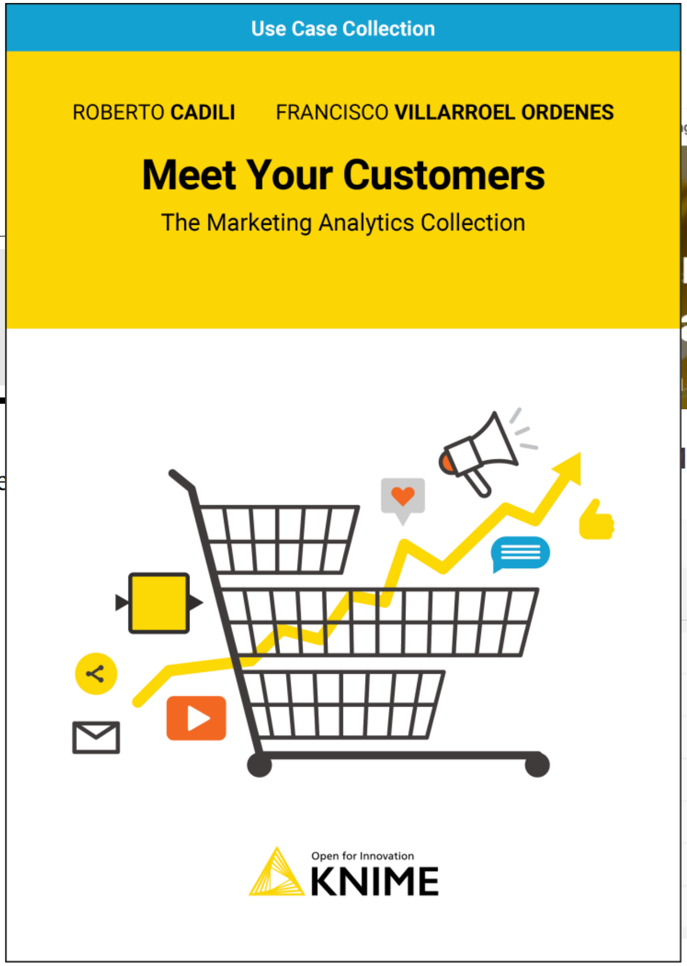

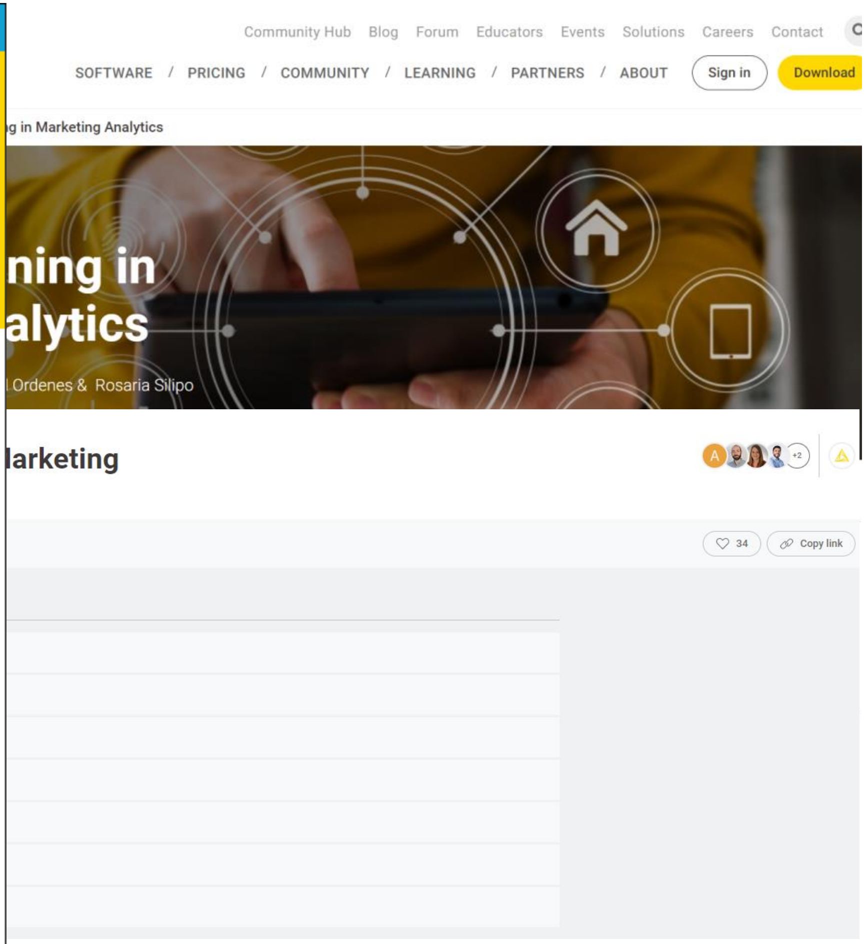

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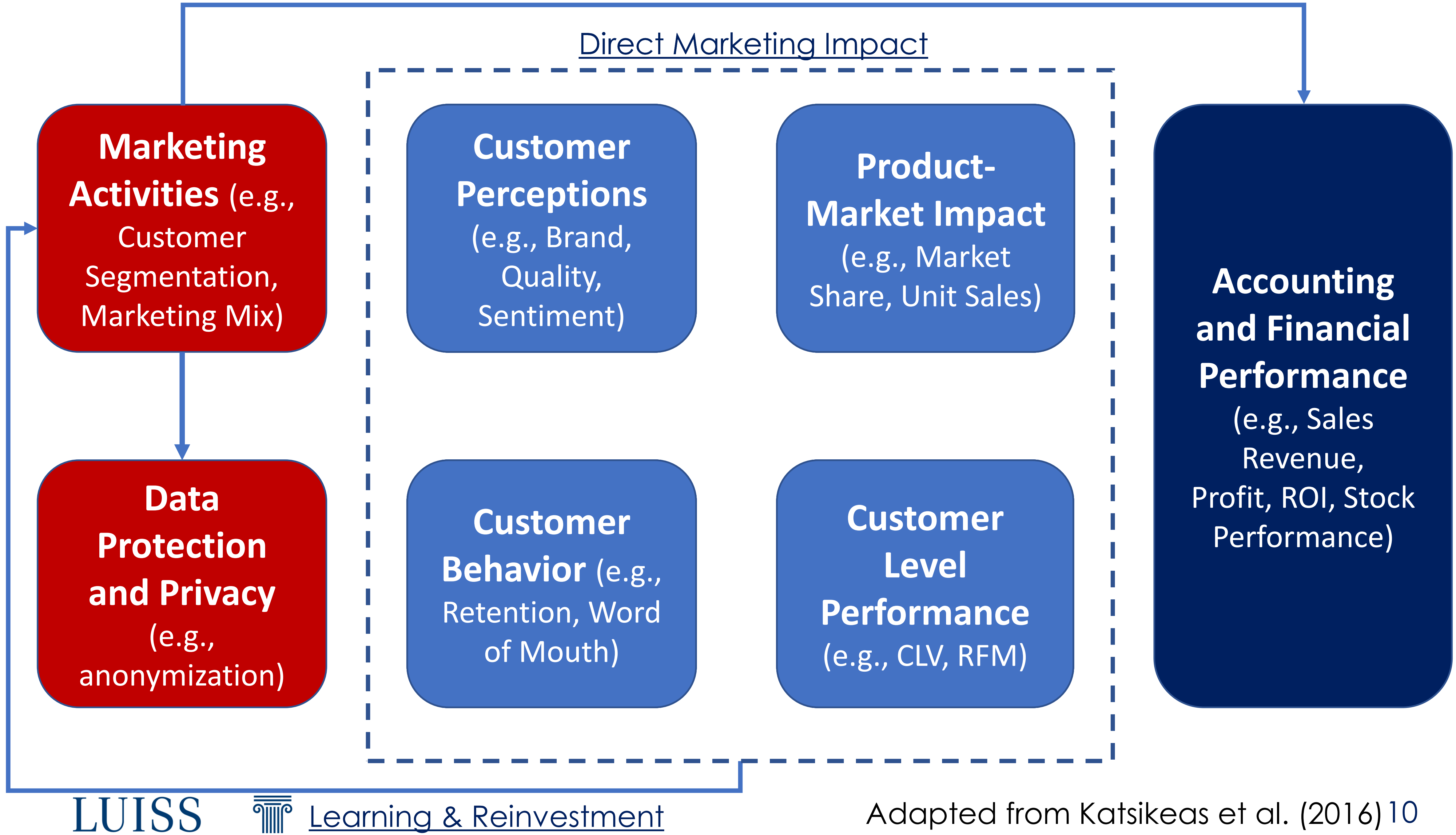
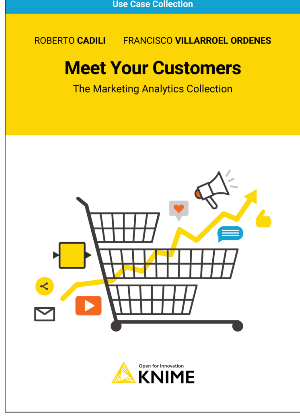


Adapted from Katsikeas et al. (2016)

Chapters and Cases



1. Segmentation and Personalization (Clustering, Rec. Systems)
2. Consumer Mindsets (**Brand Reputation,** Sentiment, SEO, CX)
3. Consumer Behavior (**Attribution,** Churn, Page Views)
4. Customer Valuation (CLV, RFM)
5. Data Protection and Privacy (Anonymization)
6. Marketing Mix (Pricing)
7. Other Analytics (**Image Analysis**, Network Analysis))

Data
(Structured & Unstructured)

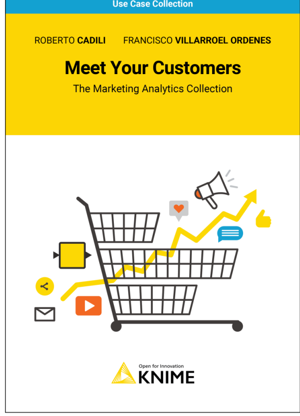
- Demographics
- Call Center
- Purchase
- Churn
- Google Analytics
- Views
- Clicks
- Purchase
- Price
- Online Reviews
- Community Forum
- Google SERP
- Tweets
- Brand Images

Models
(Statistical - NLP- ML - DL)

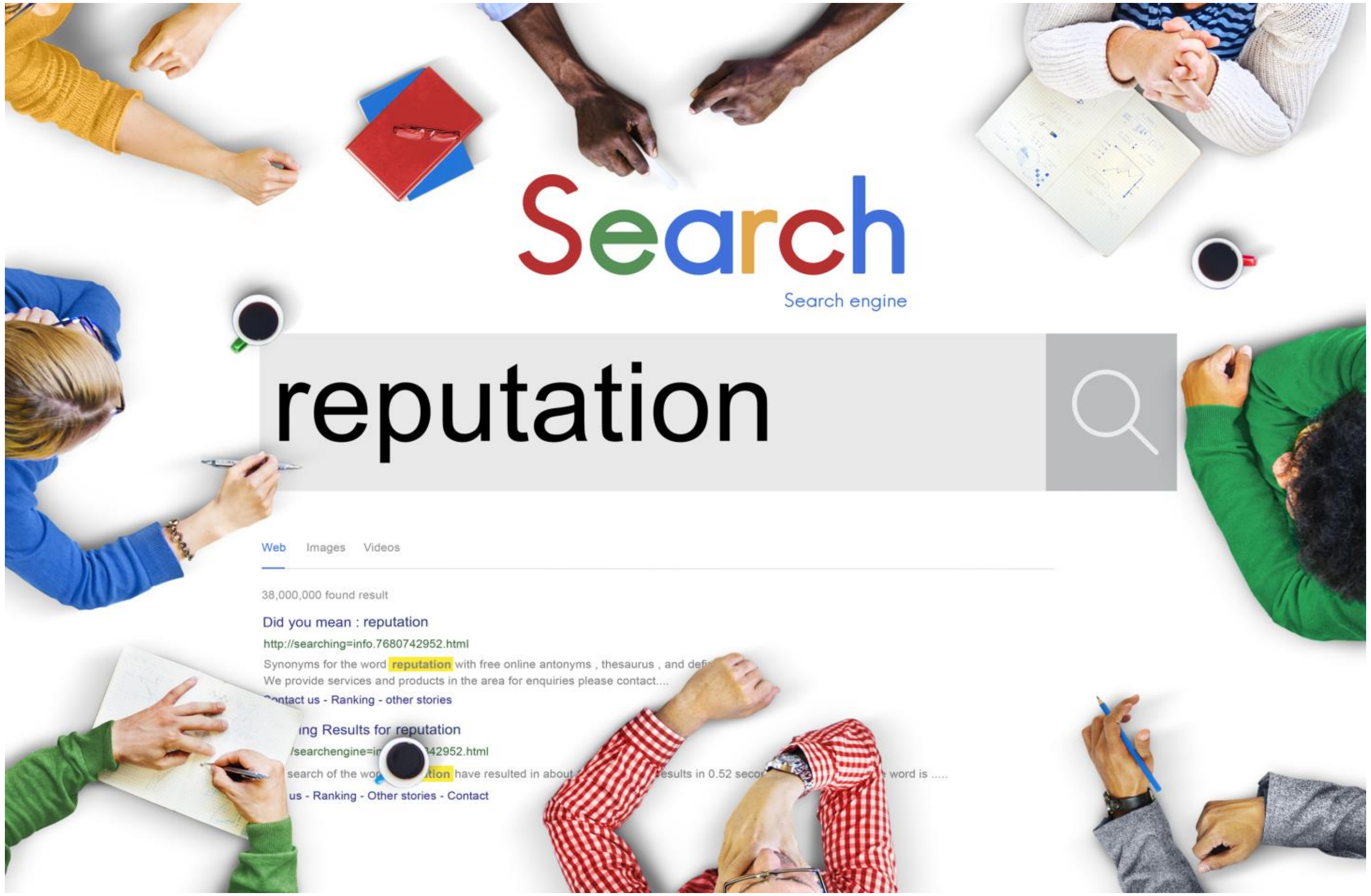
- K-means
- Association Rules
- Collaborative Filtering
- Topic Models (LDA)
- Word Embeddings
- Lexicons
- Transformer Models
- Random Forest
- CNN, SVM, NB, DT
- Shapley Value
- Logistic Regression
- Ordinal Logit Regression
- ANOVA
- CLV

Integrations
(Databases, Platforms, P. Languages)

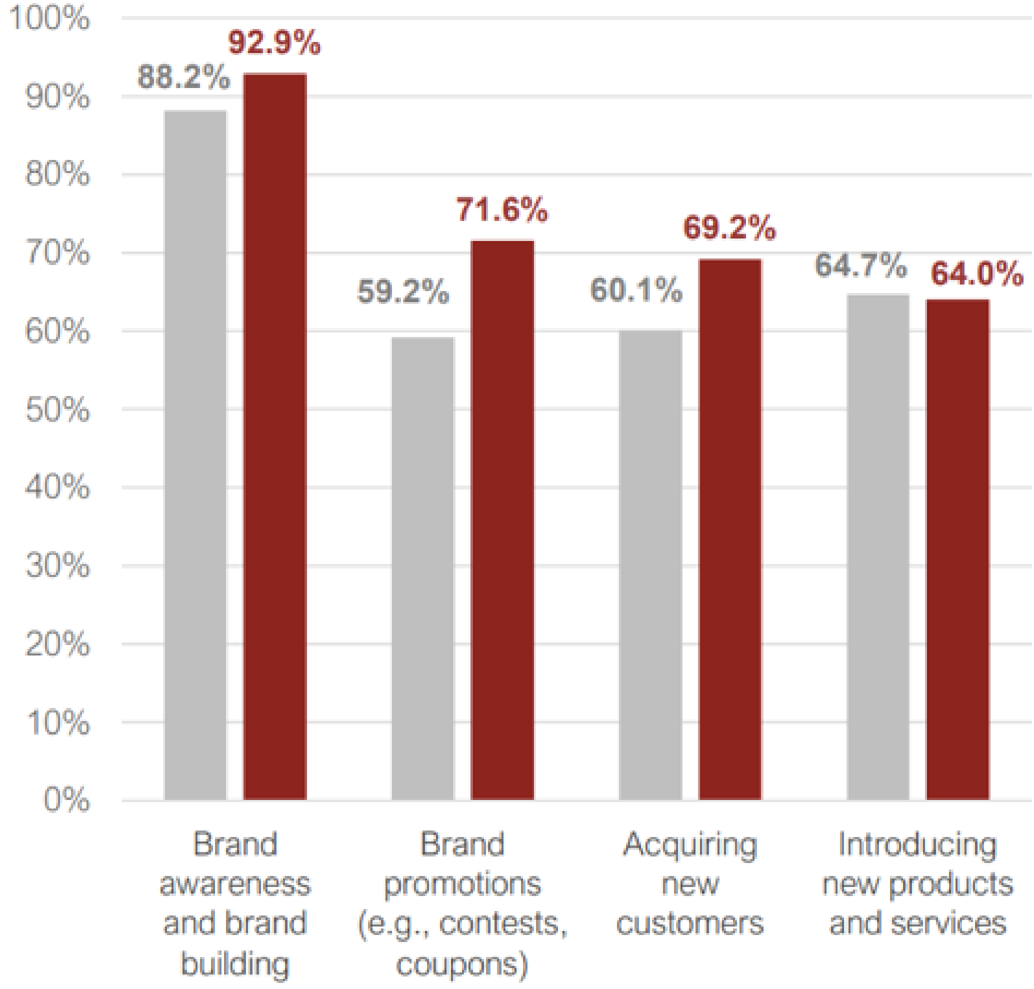
- SQL
- SAP
- Spark
- Twitter API
- Google Cloud Vision API
- Google Search API
- Google Analytics API
- R Studio (Statistics)
- Python (ImageNET)
- Keras Deep Learning
- Boilerpipe API (Scraping)
- The Color API



Case 1: Brand Reputation Tracker



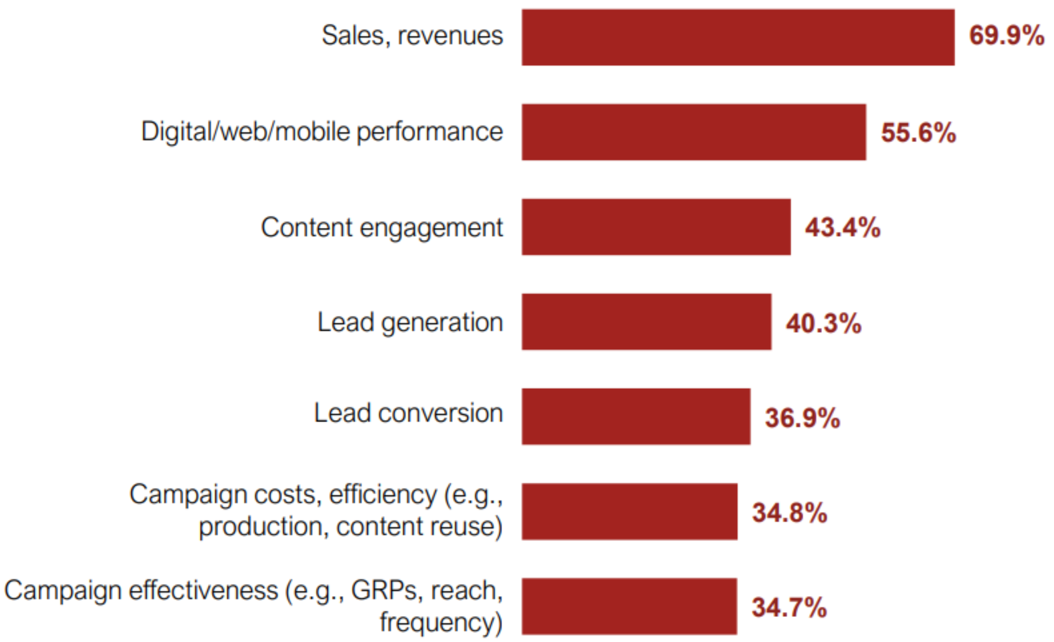
What is the main reason for using social media marketing?



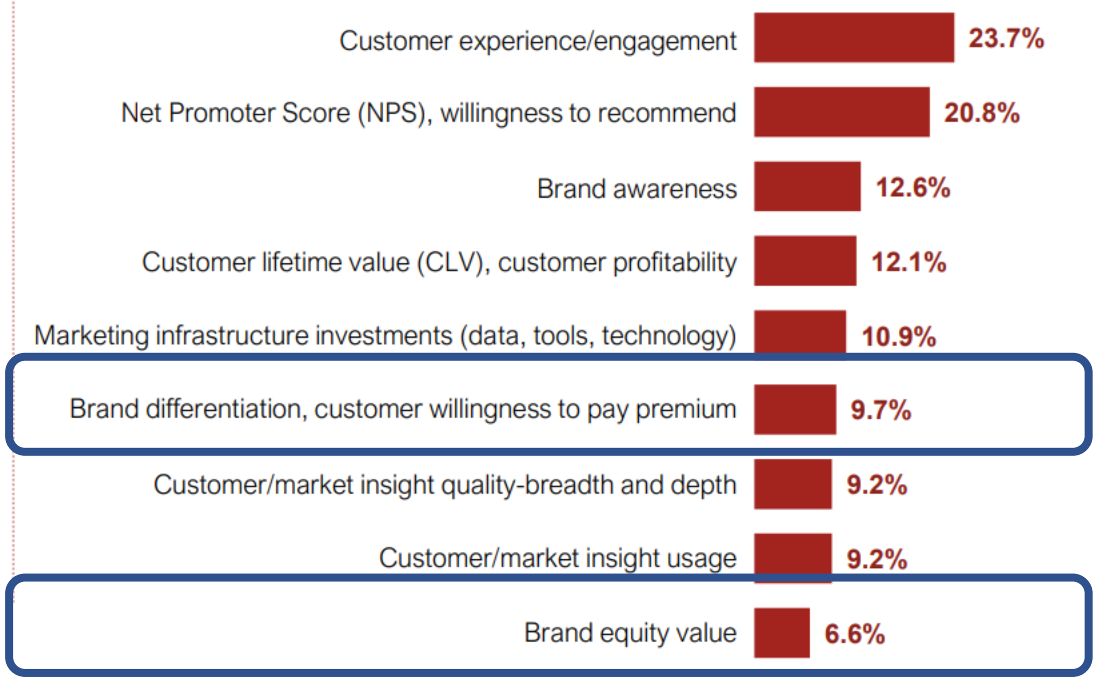
Marketing metrics send powerful signals on business impact

How consistently do you measure the following components of marketing?

Most in-use metrics



Least in-use metrics



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Brand Reputation Tracker

"Overall impression of how stakeholders think, feel, and talk about a brand. This is typically due to brand events that affect firm financial performance"

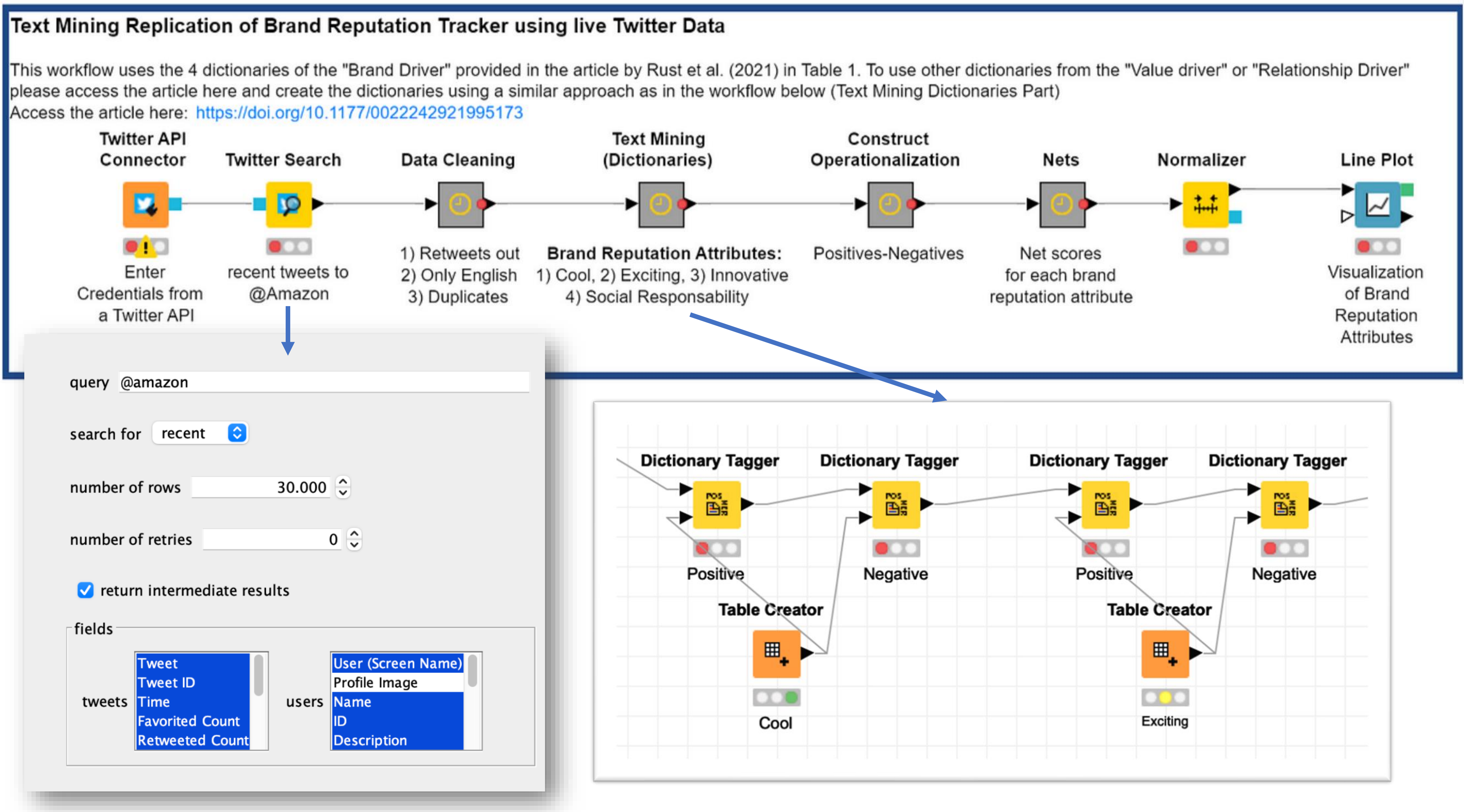
1. **Value Equity:** rational and objective aspects of a brand, such as quality and price
2. **Brand Equity:** subjective feeling that a customer has about the brand, such as brand sentiment and brand image
3. **Relationship Equity:** ties between the customer and the brand, such as community building and personal connection

Rust et al. (2021)

Brand Driver – NLP Lexicon

Table 1. Brand Reputation Drivers, Subdrivers, Descriptions, and Dictionaries.

Driver	Subdriver	Description	Positive Dictionary	Negative Dictionary
Brand	Cool	Is the brand known for being trendy, hip, awesome, cool, stylish, and sexy?	Trendi, hip, awesom, cool, modern, stylish, current, sexi	Ordinari, lame, ancient, averag
	Exciting	Does the brand bring a sense of excitement to its products/services, such as being fun, exciting, inspiring, and stimulating?	Fun, excit, inspir, happi, thrill, stimul, live, interest	Bore, dull, uninspir, tire, bland
	Innovative	Is the brand new, smart, technologically advanced, intelligent, innovative, creative, novel, and cutting edged?	New, smart, invent, advanc, cut, futurist, intellig, progress, innov, technolog, creative, novel, cutting-edg	Old, old-fashion, tradit, uninterest, outdate
	Social responsibility	Is the brand caring, benevolent, giving, and beneficial?	Benevol, give, benefici	Greedi, uncar, irrespons, evil, profit



Text Mining Replication of Brand Reputation Tracker using live Twitter Data
This workflow uses the 4 dictionaries of the "Brand Driver" provided in the article by Rust et al. (2021) in Table 1. To use other dictionaries from the "Value driver" or "Relationship Driver" please access the article here and create the dictionaries using a similar approach as in the workflow below (Text Mining Dictionaries Part)
Access the article here: https://doi.org/10.1177/0022242921995173
Twitter API Connector
Twitter Search
Data Cleaning
Text Mining (Dictionaries)
Construct Operationalization
Nets
Normalizer
Line Plot
Enter Credentials from a Twitter API
recent tweets to @Amazon
1) Retweets out
2) Only English
3) Duplicates
Brand Reputation Attributes:
1) Cool, 2) Exciting, 3) Innovative
4) Social Responsability
Positives-Negatives
Net scores for each brand reputation attribute
Visualization of Brand Reputation Attributes
query @amazon
search for recent
number of rows 30.000
number of retries 0
return intermediate results
fields
tweets
Tweet
Tweet ID
Time
Favorited Count
Retweeted Count
users
User (Screen Name)
Profile Image
Name
ID
Description
Dictionary Tagger
Dictionary Tagger
Dictionary Tagger
Dictionary Tagger
Positive
Negative
Positive
Negative
Table Creator
Table Creator
Cool
Exciting

Dior
PARIS

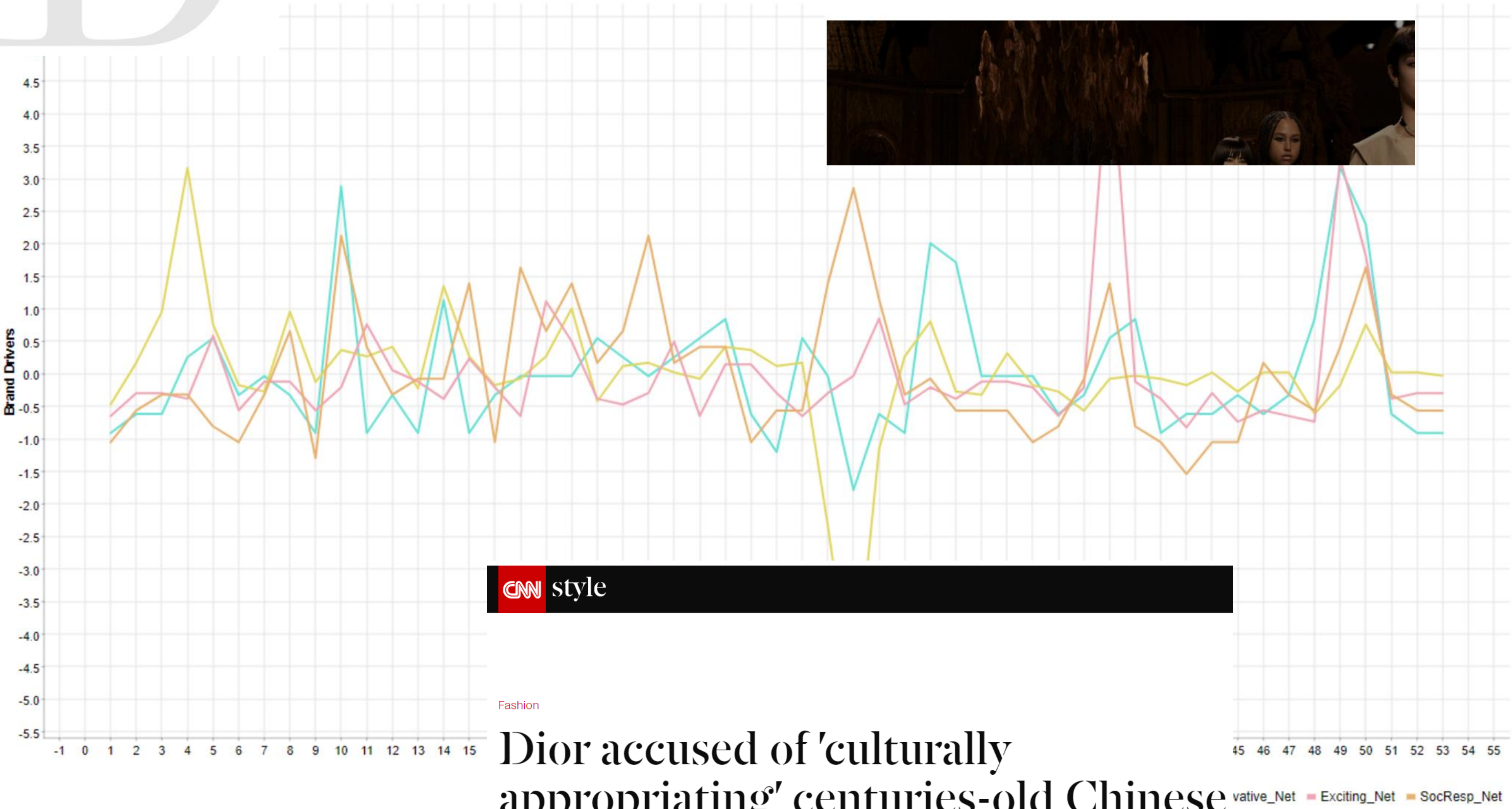
2022 Tweets about @Dior

RUNWAY SHOW: CHRISTIAN DIOR S/S 23 WOMENSWEAR

PUBLISHED ON 27 SEPTEMBER 2022

Watch the Christian Dior S/S 23 womenswear show in Paris.

SHARE
TWITTER
FACEBOOK



CNN style

Fashion

Dior accused of 'culturally appropriating' centuries-old Chinese skirt

Published 29th July 2022

LUISS

Case 2: Marketing Attribution

Methods for Measuring Attribution

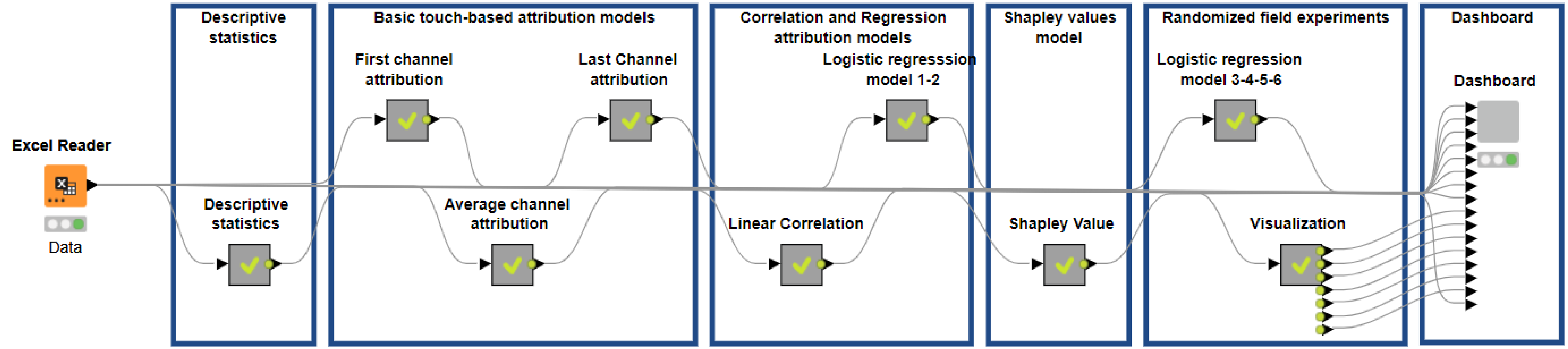
- Touch-based attribution (e.g., First Channel, Last Channel)
- Logistic Regression Models
- Shapley Value (What happens if removing one channel?)
- Random Field Experiments
- Markov Chain Models

Attribution Modelling

This workflow is based on the book chapter "Attribution Modelling" by de Haan (2022). It replicates the analysis of the book chapter using KNIME Analytics with R integration nodes.

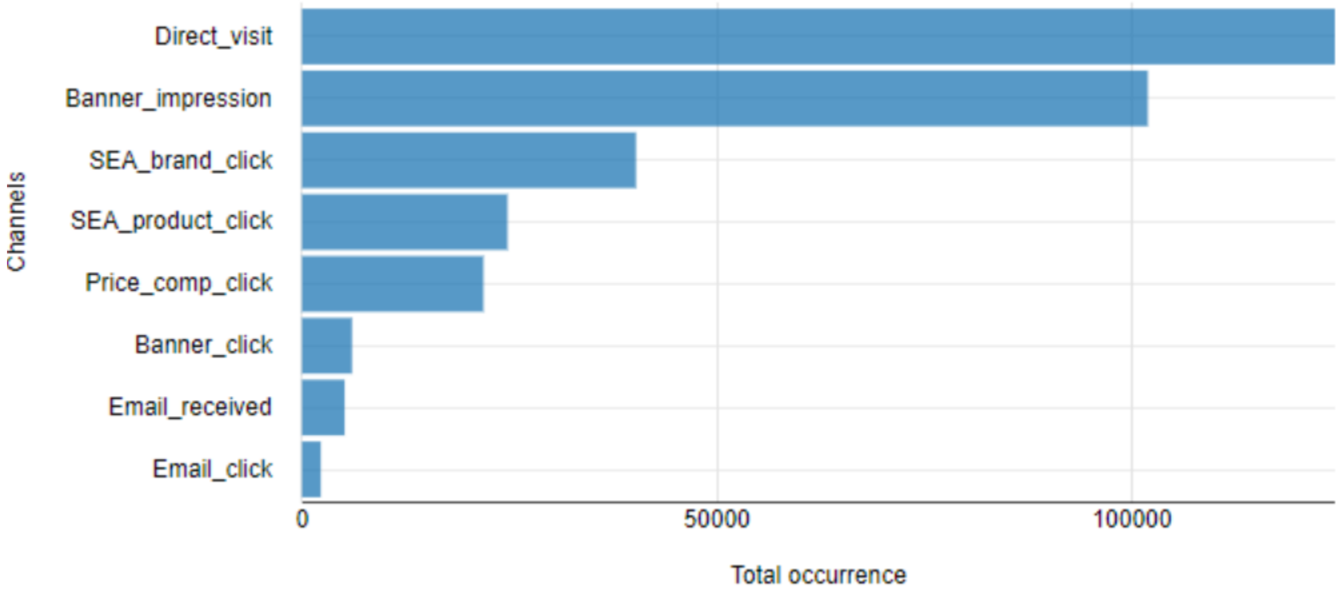
After a brief overview of the data with descriptive statistics, the workflow follows the aforementioned book chapter by running through again the different attribution models analyzed in this work, from the simplest ones (i.e. first channel attribution) to more complex models like the Shapley values-based attribution method. The workflow is then completed with an interactive dashboard reporting all the visualizations produced.

Attribution modeling is a relevant field of research for marketers as it alllows them to give the correct credit to the contribution made by each channel along a customer journey . It improves marketers´ability to outline what are the most decisive channels in a customer journey that concludes in a conversion (i.e. a purchase, a click, a subscription), making more efficient the budgeting-allocation process.



Total occurrence per channel

Barchart representing most frequent touchpoints between a firm and its customers or potential customers

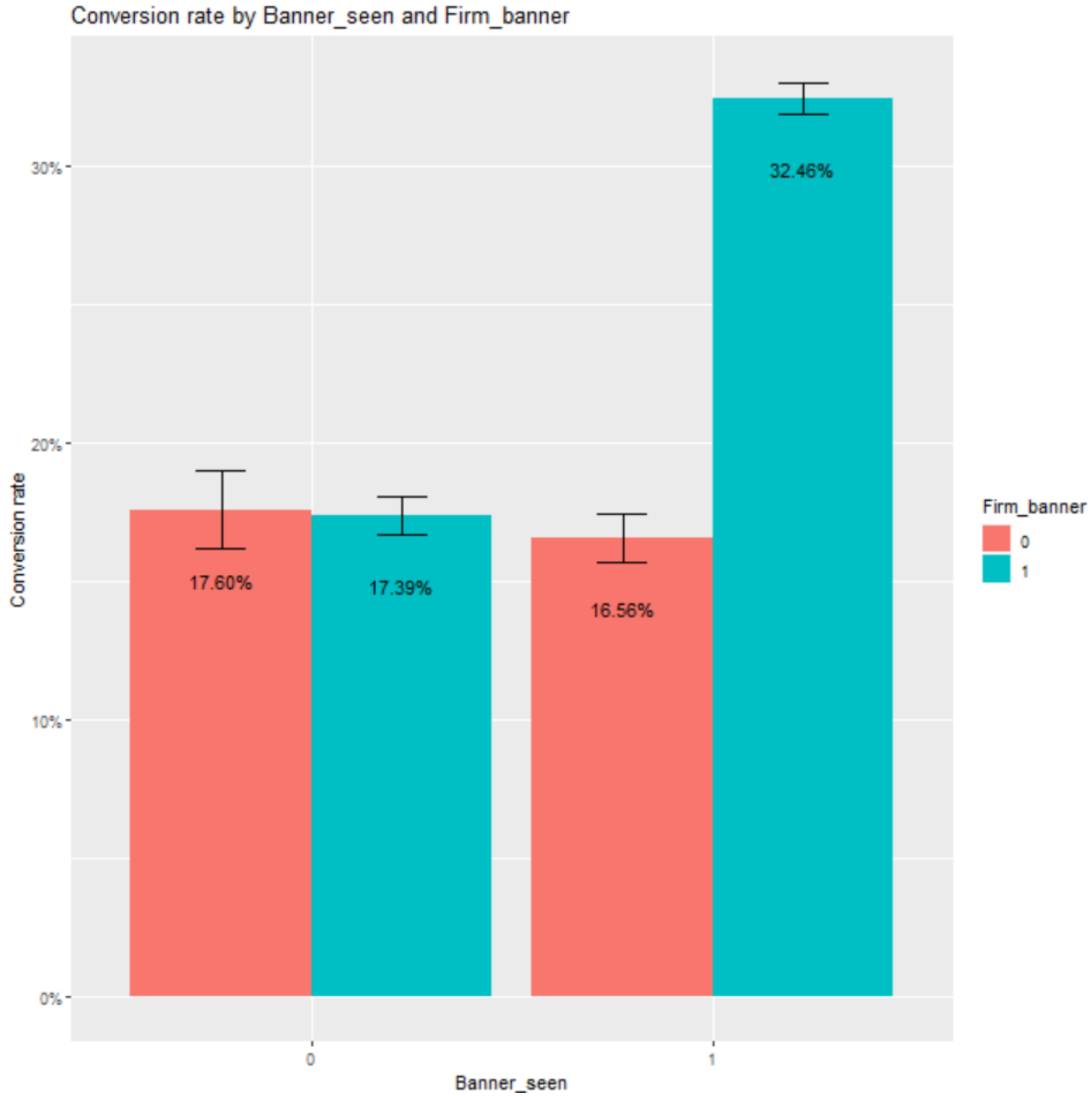


Shapley values based attribution model

It shows the incremental effect of each additional touchpoint in the customer journey

Clear Sorting

Customer_path	Conversion_probability	Missing_Channel_Impact
Banner + SEA_Brand + SEA_Product	16.28%	0.0%
SEA_Brand + SEA_Product	7.49%	8.79%
Banner + SEA_Brand	11.8%	4.48%
Banner + SEA_Product	5.96%	10.32%

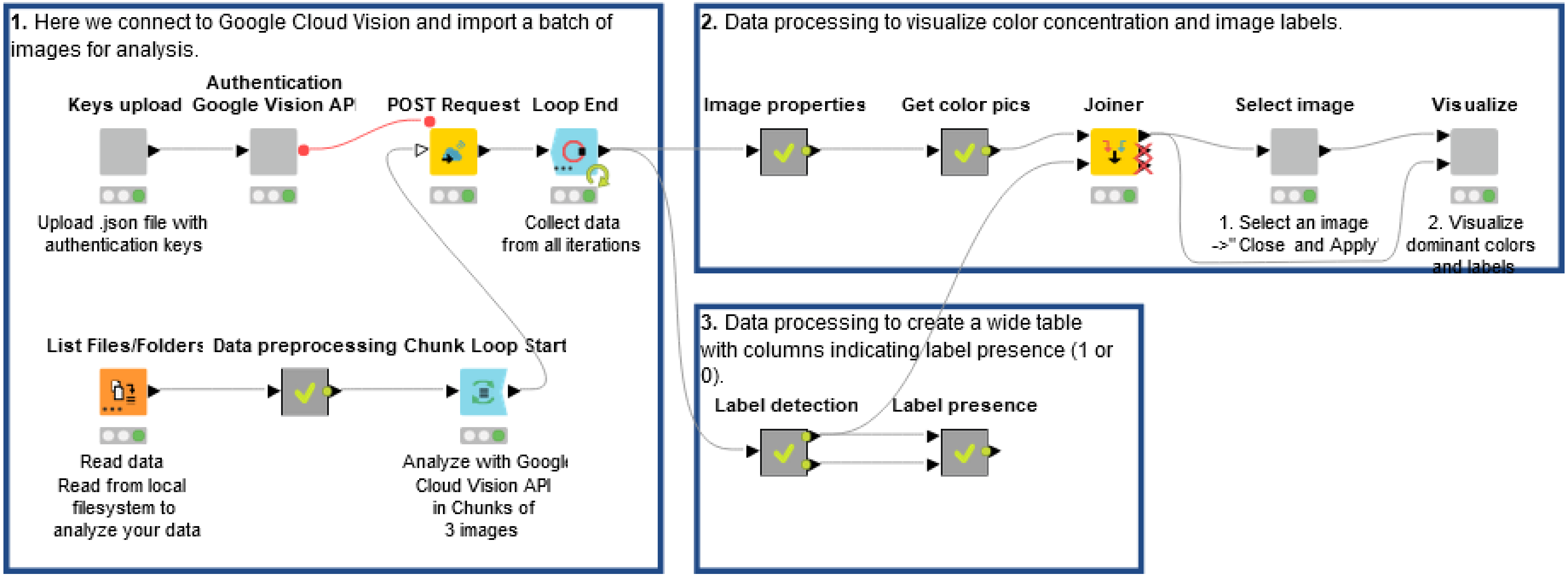


Case 3: Image Analytics for Marketing

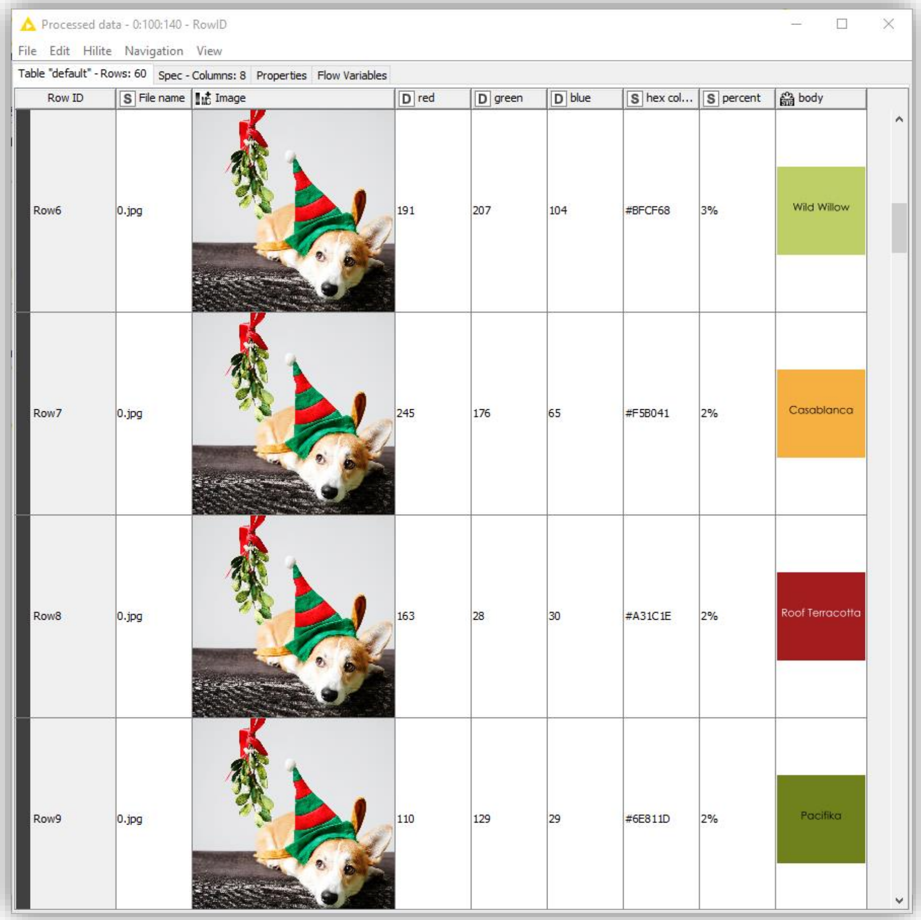
"74% of the content generated by users and firms contains some form of visual elements, including photos, illustrations, videos, and data visualization" (Vengage 2021)

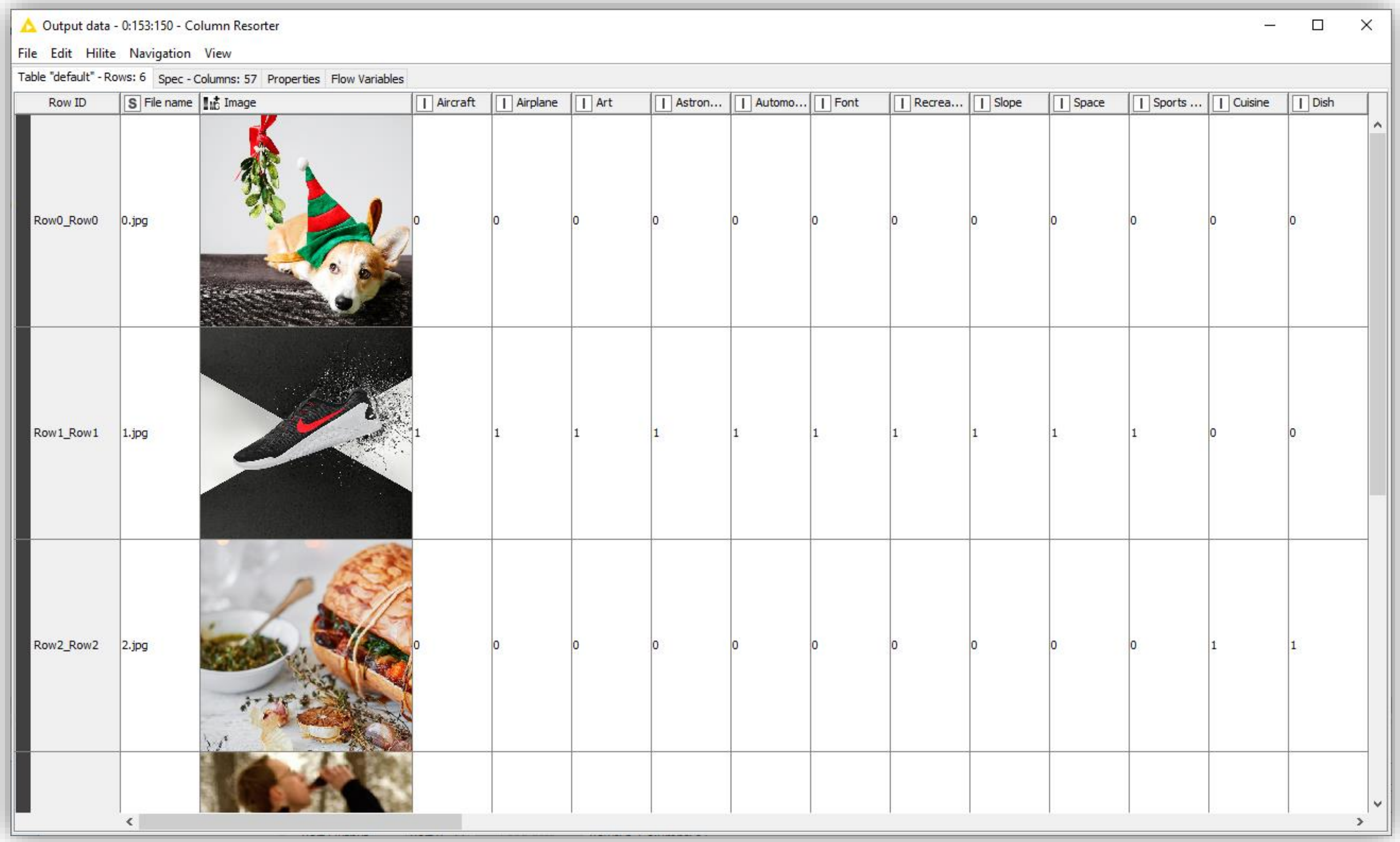
How to craft **engaging content** to compete in today's attention economy?

Google Vision API



Marketers can analyze batches of photos about their content, the competition, or their customers





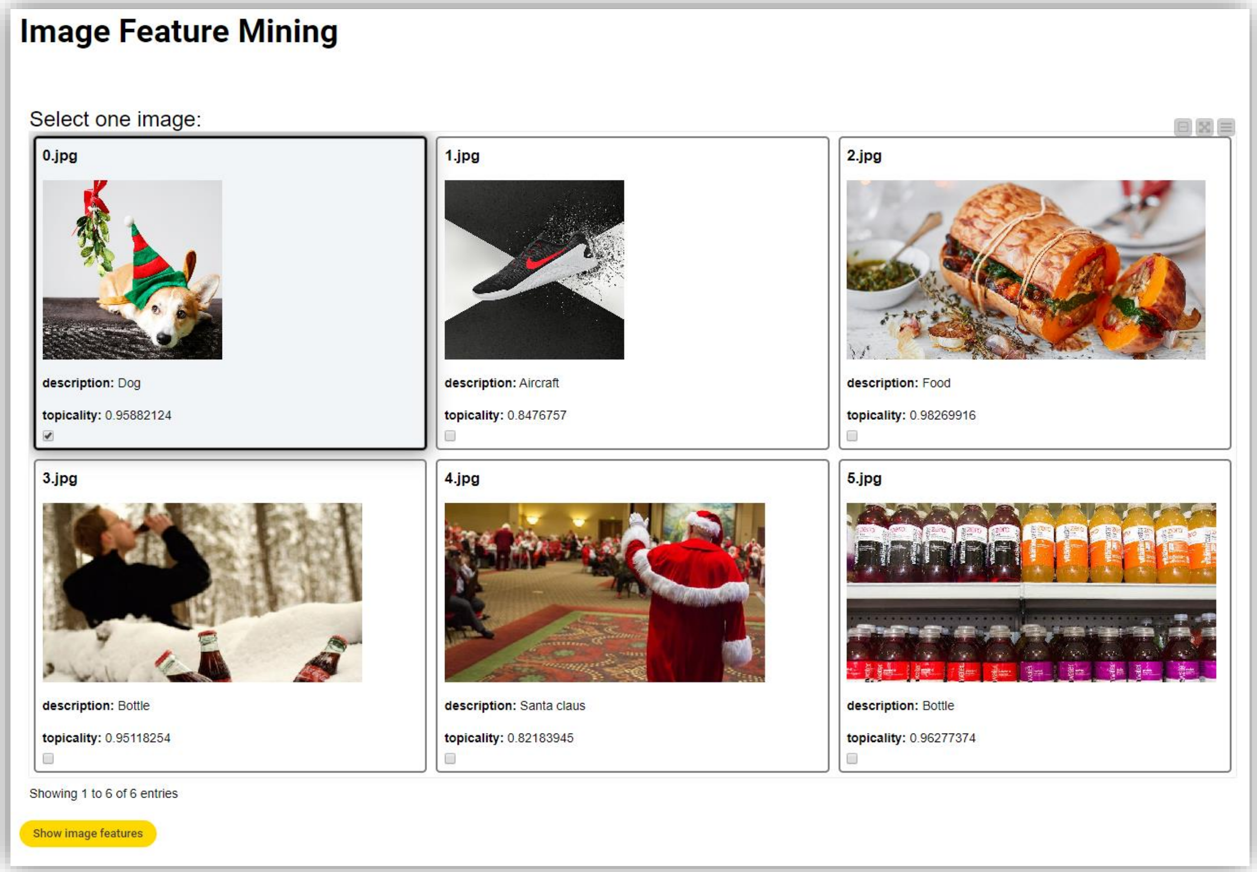
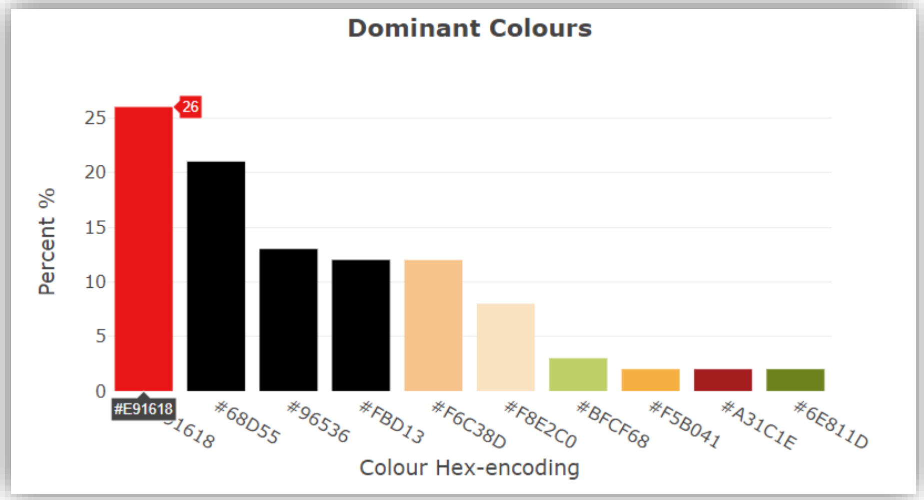
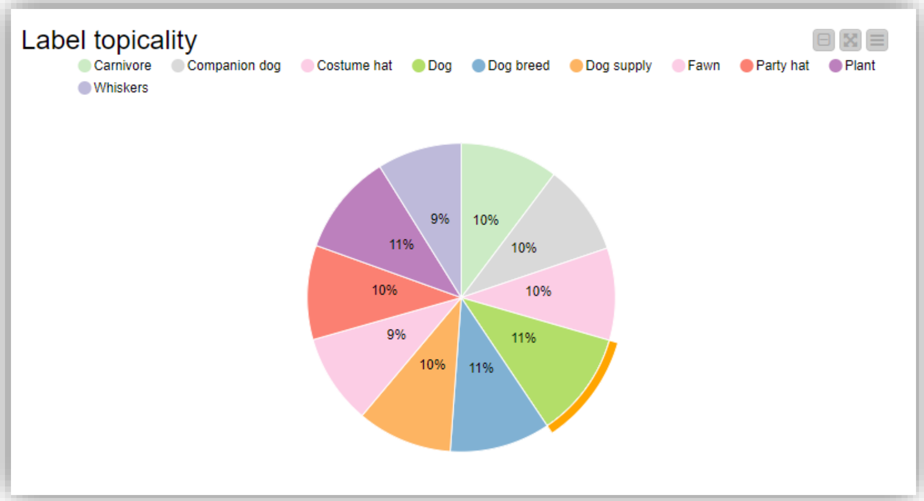


Image Feature Mining
Select one image:
0.jpg
description: Dog
topicality: 0.95882124
1.jpg
description: Aircraft
topicality: 0.8476757
2.jpg
description: Food
topicality: 0.98269916
3.jpg
description: Bottle
topicality: 0.95118254
4.jpg
description: Santa claus
topicality: 0.82183945
5.jpg
description: Bottle
topicality: 0.96277374
Showing 1 to 6 of 6 entries
Show image features


Dominant Colours
Percent %
0
5
10
15
20
25
26
#E91618
#68D55
#96536
#FBD13
#F6C38D
#F8E2C0
#BFCF68
#F5B041
#A31C1E
#6E811D
Colour Hex-encoding


Label topicality
Carnivore
Companion dog
Costume hat
Dog
Dog breed
Dog supply
Fawn
Party hat
Plant
Whiskers
9%
10%
10%
10%
11%
11%
10%
9%
10%
11%

Ongoing Projects. "Image Dynamism"

"Images can generate perceptions of movement, which can increase consumer attention and engagement"

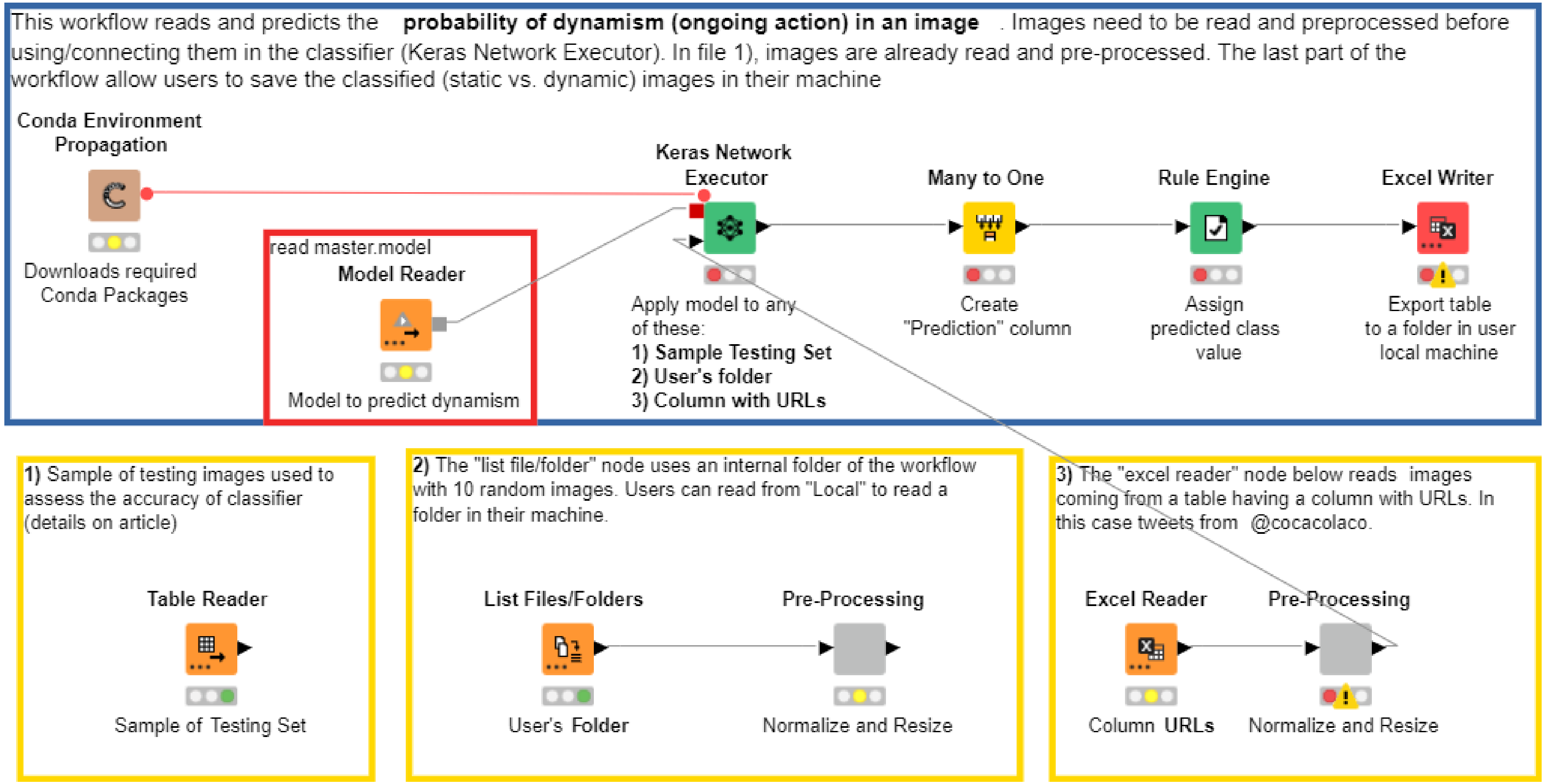
Dynamic Images



Static Images


(Roggeveen et al. 2015)

Image Dynamism Classifier

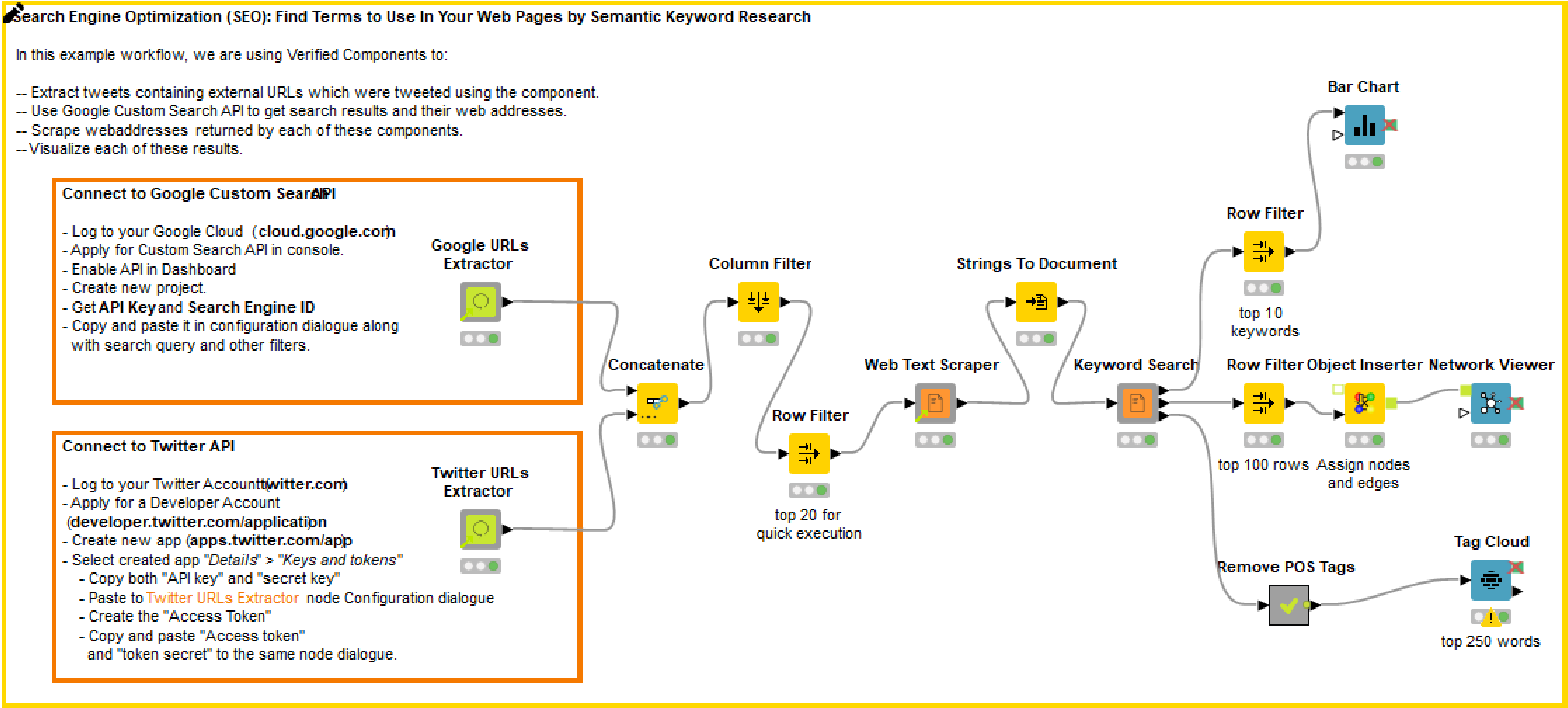


Thank you for your attention!

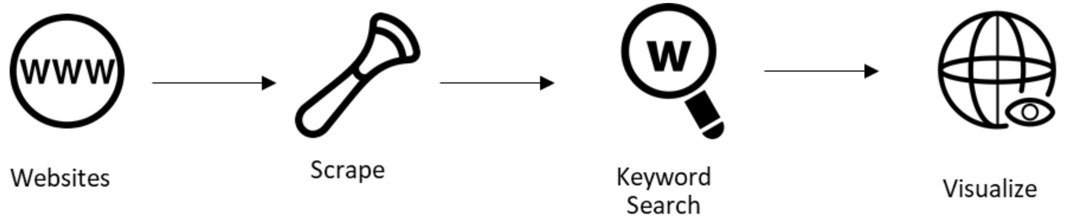
fvillarroel@luiss.it

Case 4: SEO

- Search engines (e.g. Google) rank web pages and brand content, according to the presence of **keywords** that are conceptually or semantically related.
- How can marketers make their web pages stand out to search engines and make it easy to find to public?

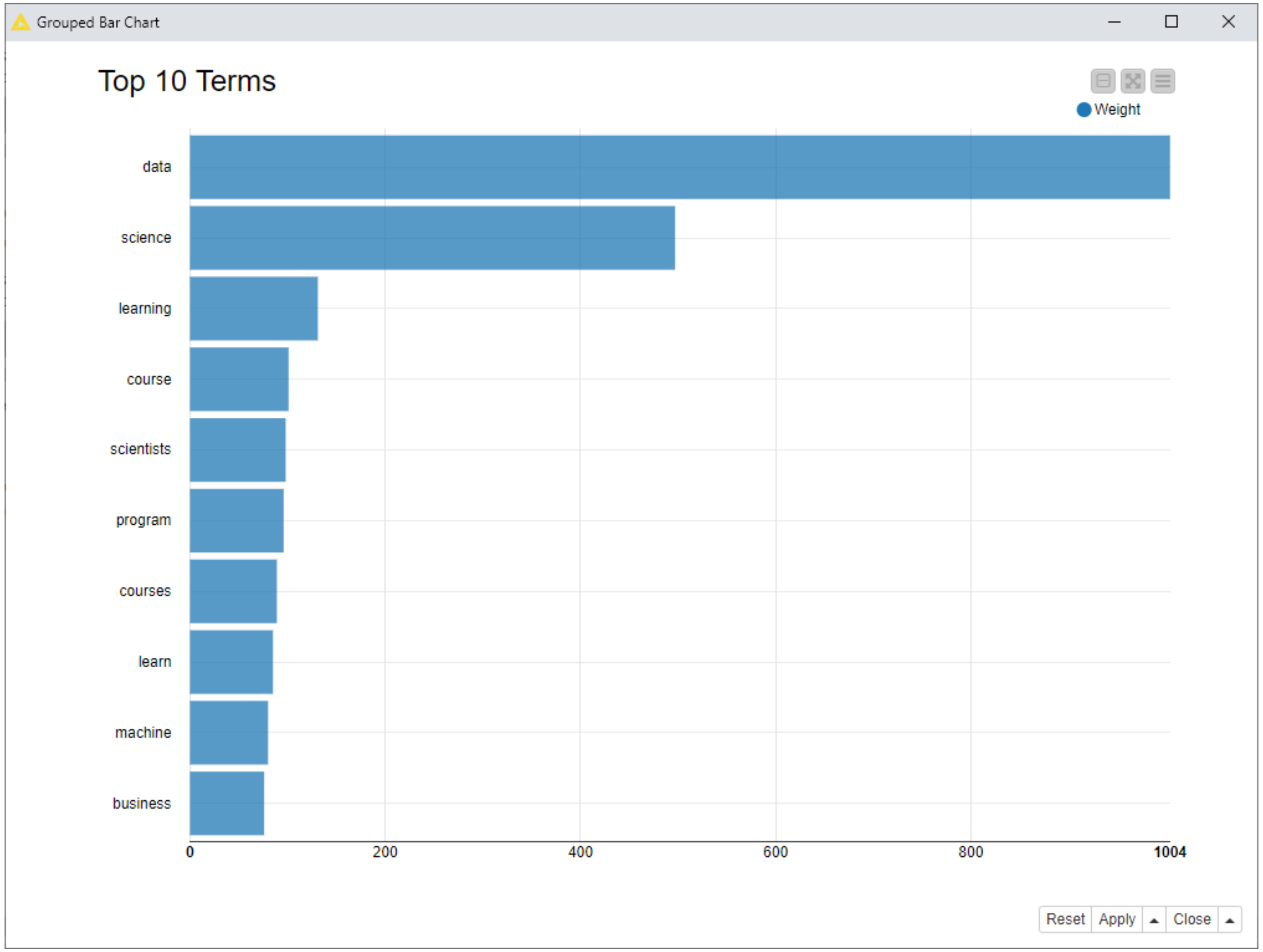


Search Engine Optimization (SEO): Find Terms to Use In Your Web Pages by Semantic Keyword Research
In this example workflow, we are using Verified Components to:
-- Extract tweets containing external URLs which were tweeted using the component.
-- Use Google Custom Search API to get search results and their web addresses.
-- Scrape webaddresses returned by each of these components.
--Visualize each of these results.
Connect to Google Custom SearAPI
- Log to your Google Cloud (cloud.google.com)
- Apply for Custom Search API in console.
- Enable API in Dashboard
- Create new project.
- Get API Key and Search Engine ID
- Copy and paste it in configuration dialogue along with search query and other filters.
Google URLs Extractor
Connect to Twitter API
- Log to your Twitter Account (twitter.com)
- Apply for a Developer Account (developer.twitter.com/application)
- Create new app (apps.twitter.com/app)
- Select created app "Details" > "Keys and tokens"
- Copy both "API key" and "secret key"
- Paste to Twitter URLs Extractor node Configuration dialogue
- Create the "Access Token"
- Copy and paste "Access token" and "token secret" to the same node dialogue.
Twitter URLs Extractor
Concatenate
Column Filter
Row Filter
top 20 for quick execution
Web Text Scraper
Strings To Document
Keyword Search
Row Filter
top 10 keywords
Bar Chart
Row Filter
top 100 rows
Object Inserter
Assign nodes and edges
Network Viewer
Remove POS Tags
Tag Cloud
top 250 words

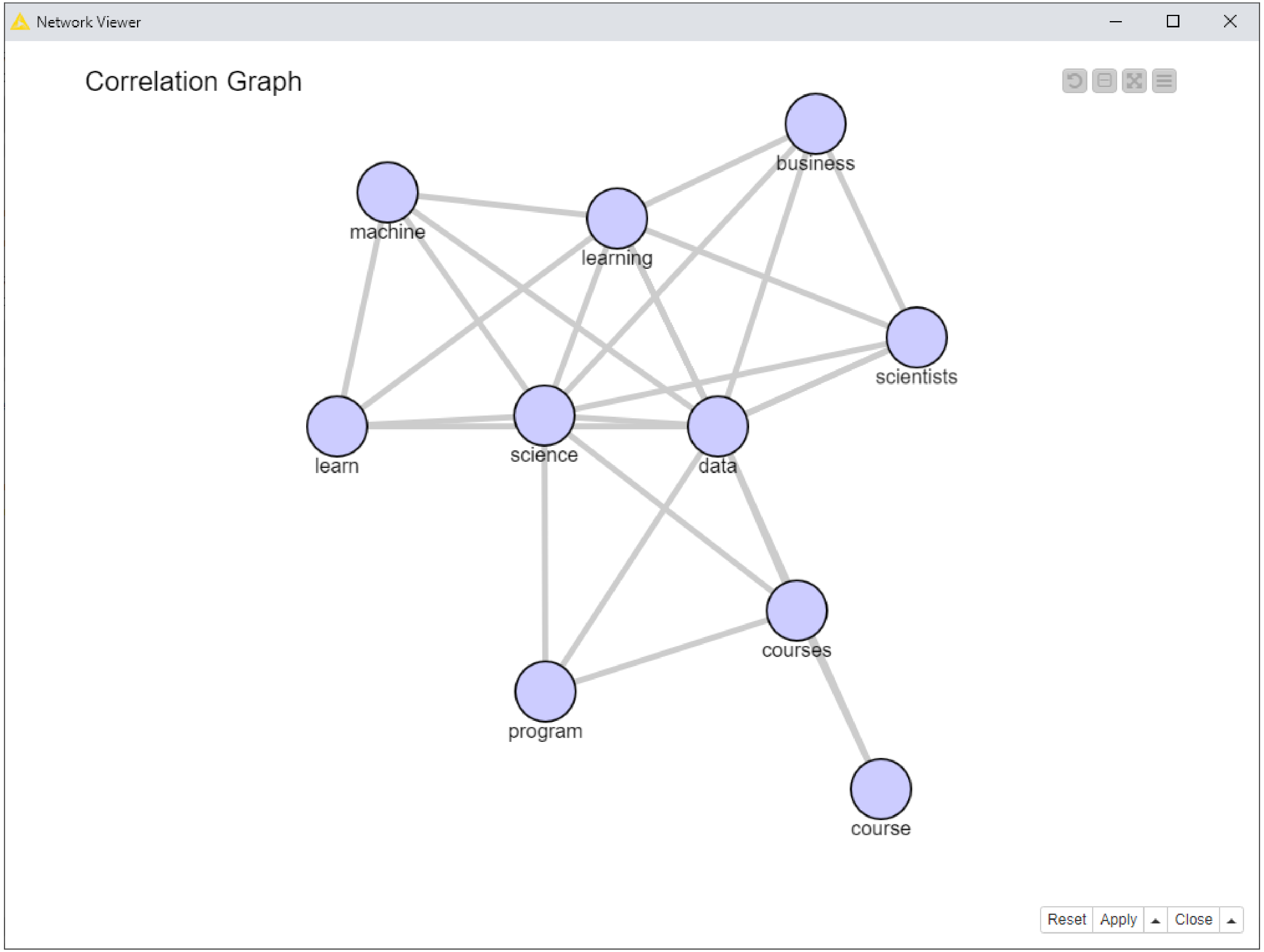


Websites
Scrape
Keyword Search
Visualize

Most frequent single keywords



Top descriptive keywords from LDA



Most frequently co-occurring words

Case 5: Sentiment Analysis

Lexicon-based

Using dictionaries and grammar rules to understand the sentiment.

Example:

Negative words vs. Positive words in a review

Negations to change the polarity of the word sentiment

Introduce more complex grammar constructs to understand the exact sentiment in the sentence.

I did not say that I do not like those shoes.

Traditional ML

Using the classic Machine Learning Construct:

- An application to train a ML model
- An application to deploy the ML model

Core ML as of:

- Decision trees and tree-based ensemble algorithms
- SVM
- Regressions
- And so on …

LSTM (Deep Learning)

Using LSTM units within a neural network to exploit the sequential character of text.

This architecture has the added benefit of incorporating grammar rules, like negations.

The longer the input of past words/characters, the more complex the grammar structure that we can introduce.

BERT (Deep Learning)

BERT are Google pre-trained neural transformers.

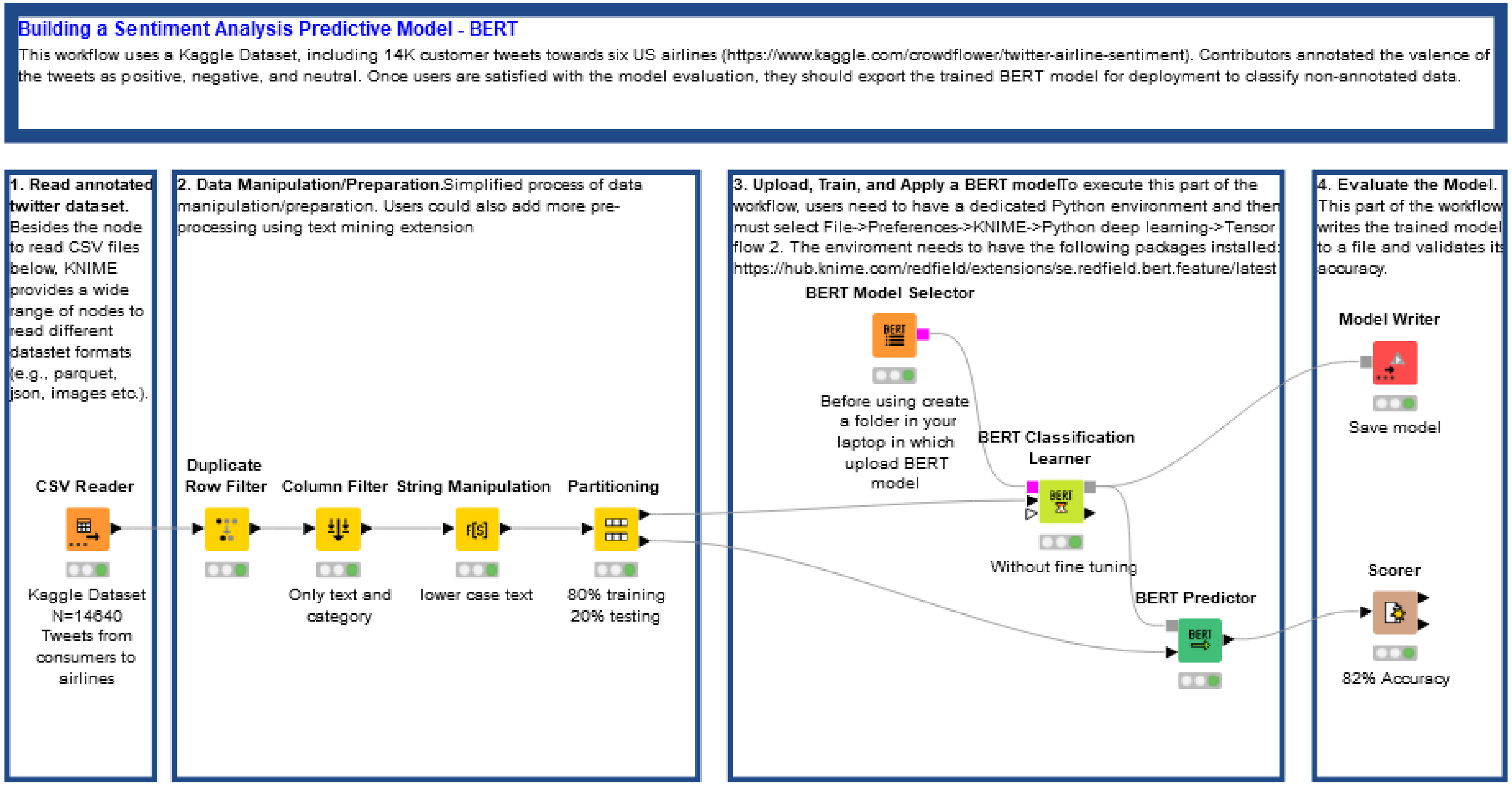
Advantages:

- They are pretrained
- On Google data

Disadvantages:

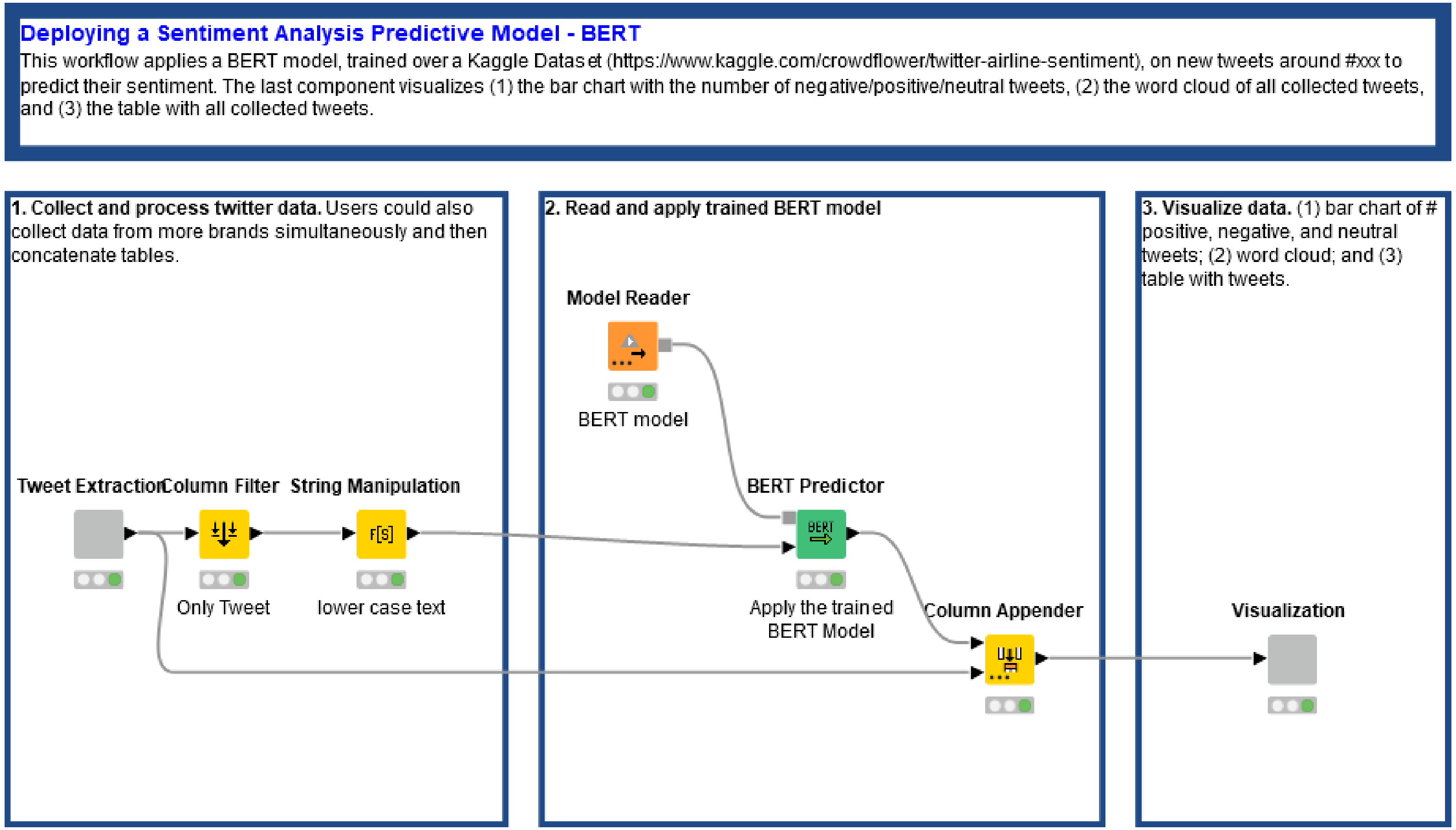
- They reside somewhere externally

Training



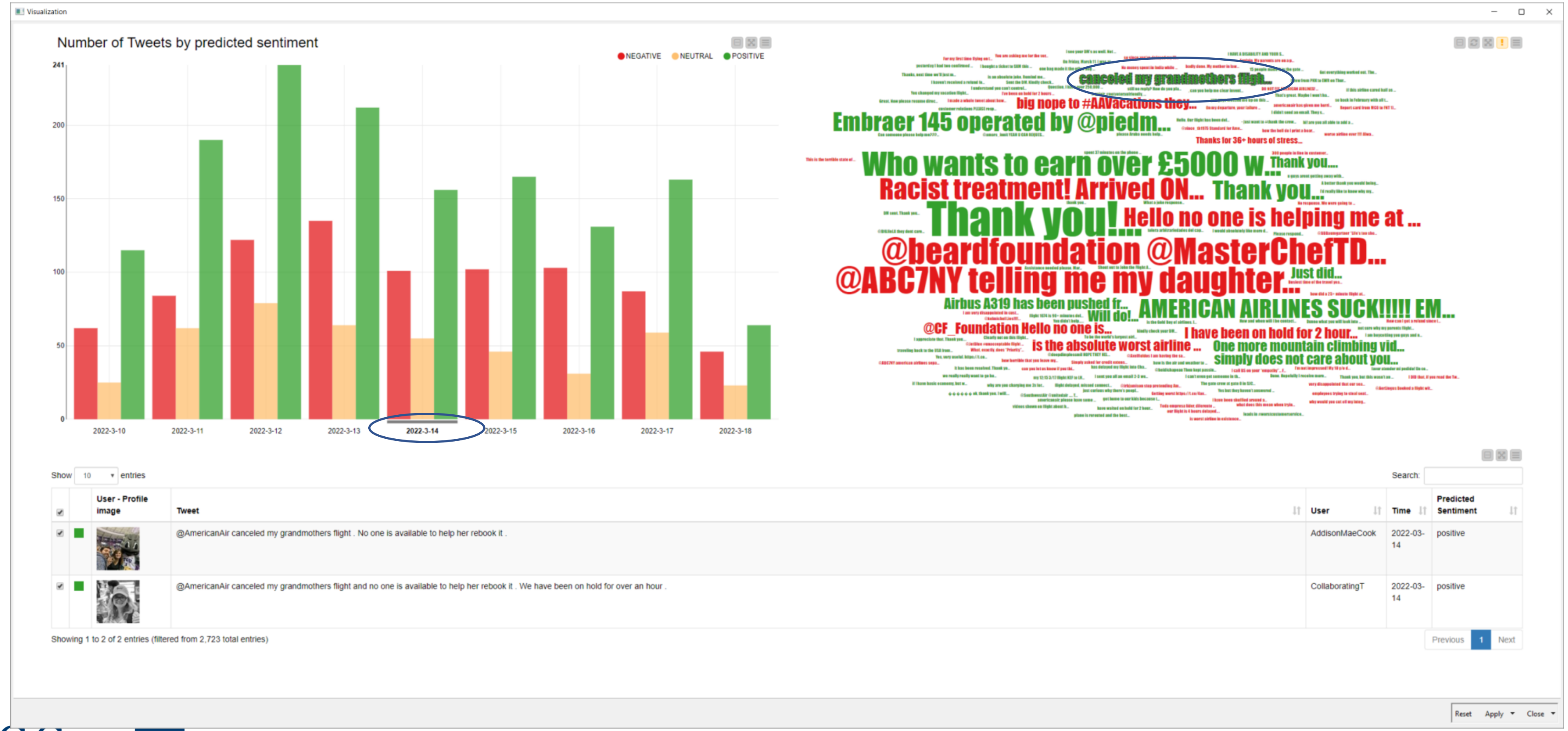
Building a Sentiment Analysis Predictive Model - BERT
This workflow uses a Kaggle Dataset, including 14K customer tweets towards six US airlines (https://www.kaggle.com/crowdflower/twitter-airline-sentiment). Contributors annotated the valence of the tweets as positive, negative, and neutral. Once users are satisfied with the model evaluation, they should export the trained BERT model for deployment to classify non-annotated data.
1. Read annotated twitter dataset. Besides the node to read CSV files below, KNIME provides a wide range of nodes to read different datastet formats (e.g., parquet, json, images etc.).
CSV Reader
Kaggle Dataset N=14640 Tweets from consumers to airlines
2. Data Manipulation/Preparation.Simplified process of data manipulation/preparation. Users could also add more pre-processing using text mining extension
Duplicate Row Filter
Column Filter
String Manipulation
Partitioning
Only text and category
lower case text
80% training 20% testing
3. Upload, Train, and Apply a BERT modelTo execute this part of the workflow, users need to have a dedicated Python environment and then must select File->Preferences->KNIME->Python deep learning->Tensor flow 2. The enviroment needs to have the following packages installed: https://hub.knime.com/redfield/extensions/se.redfield.bert.feature/latest
BERT Model Selector
Before using create a folder in your laptop in which upload BERT model
BERT Classification Learner
Without fine tuning
BERT Predictor
4. Evaluate the Model. This part of the workflow writes the trained model to a file and validates its accuracy.
Model Writer
Save model
Scorer
82% Accuracy

Deployment


Deploying a Sentiment Analysis Predictive Model - BERT
This workflow applies a BERT model, trained over a Kaggle Dataset (https://www.kaggle.com/crowdflower/twitter-airline-sentiment), on new tweets around #xxx to predict their sentiment. The last component visualizes (1) the bar chart with the number of negative/positive/neutral tweets, (2) the word cloud of all collected tweets, and (3) the table with all collected tweets.
1. Collect and process twitter data. Users could also collect data from more brands simultaneously and then concatenate tables.
Tweet Extraction
Column Filter
String Manipulation
Only Tweet
lower case text
2. Read and apply trained BERT model
Model Reader
BERT model
BERT Predictor
Apply the trained BERT Model
Column Appender
3. Visualize data. (1) bar chart of # positive, negative, and neutral tweets; (2) word cloud; and (3) table with tweets.
Visualization

Sentiment Analysis: The Results

Lexicon-based | Core ML | LSTM (Deep Learning) | BERT (Deep Learning)

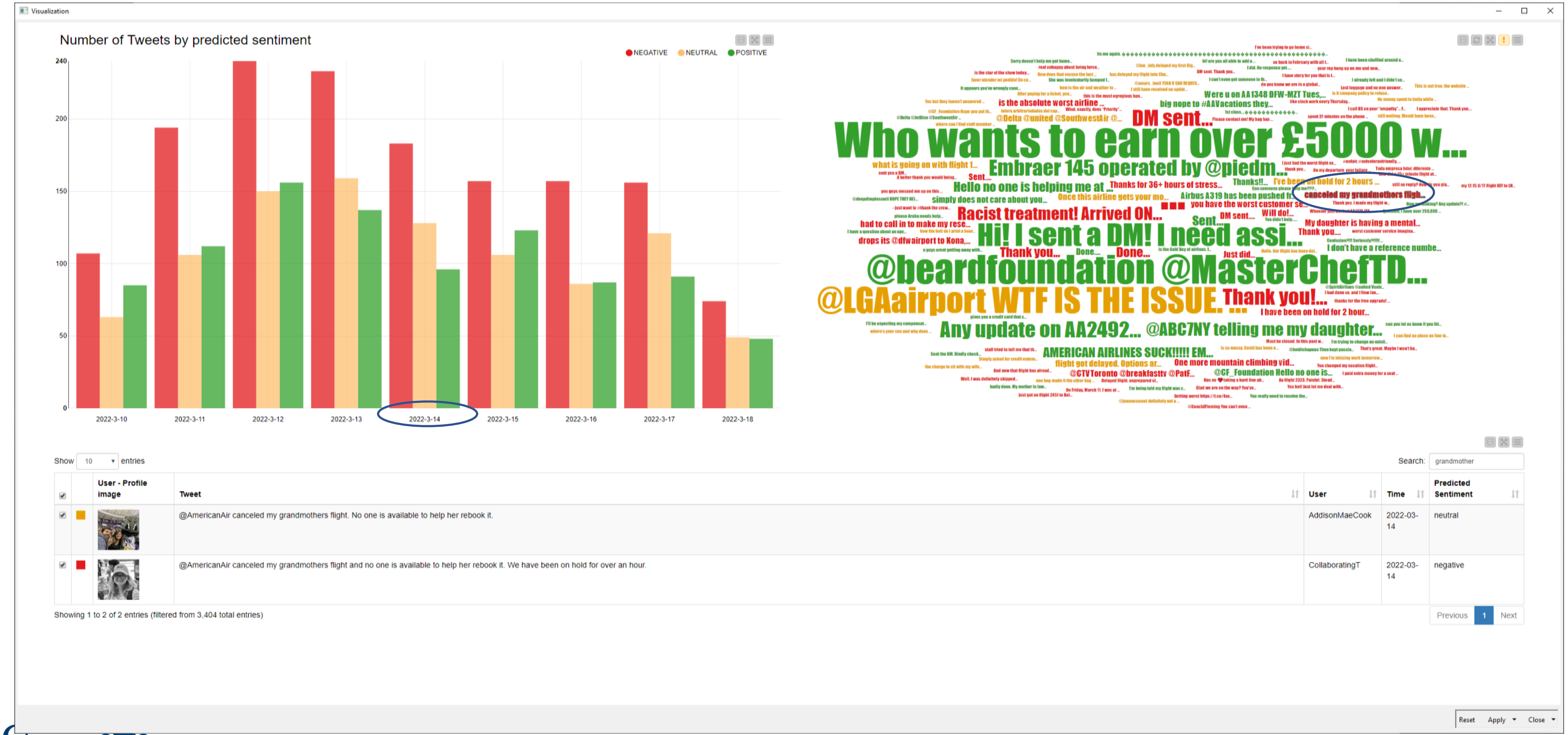


Sentiment Analysis: The Results

Lexicon-based	Core ML (SVM)	LSTM (Deep Learning)	BERT (Deep Learning)

Sentiment Analysis: The Results

Lexicon-based | Core ML (SVM) | **LSTM (Deep Learning)** | BERT (Deep Learning)



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Sentiment Analysis: The Results

Lexicon-based	Core ML (SVM)	LSTM (Deep Learning)	BERT (Deep Learning)