Semantic Visions ESG Index

Created by: Lukáš Gábor, Adam Goldstein, Austin Yang, Sam Salvati

Team

Lukáš Gábor

Lukáš is a data enthusiast who made a successful transition from academia to the private sector. His expertise lies in consulting projects with a specific focus on ESG, data analytics, and predictive modeling. Driven by his passion for data, Lukáš is dedicated to leveraging its potential to bring about positive change and promote sustainable business practices. He actively engages in topics and projects that align with his vision of a more sustainable future.

#ESG
#predictionModeling
#bigData

Adam Goldstein

Adam is a Data Theory Major at the University of California, Los Angeles. He possesses a profound understanding of mathematics, data analytics, and business. His vision is to merge his entrepreneurial experience with his technical expertise, forging a compelling career path that leverages both skill sets.

#DataTheory
#Math
#Statistics

Austin Yang

Austin is a Math of Computation major at the University of California, Los Angeles. He has worked in the past as a data analyst and machine learning engineer at a computer vision startup. He is passionate about and proficient in math, data analytics, and machine learning, and he hopes to be able to translate these passions into a future career.

#Math
#MachineLearning
#Data

Samuel Salvati

Sam is entering his fourth year as a Math/Economics major at the University of California, Los Angeles. He has interned as a marketing strategist, business analyst, legal researcher, and data analyst. His robust understanding of economics, mathematics, and business analytics combined with his drive to learn and grow in his work environment make him well suited for his transition to the professional world.

#Math
#Economics

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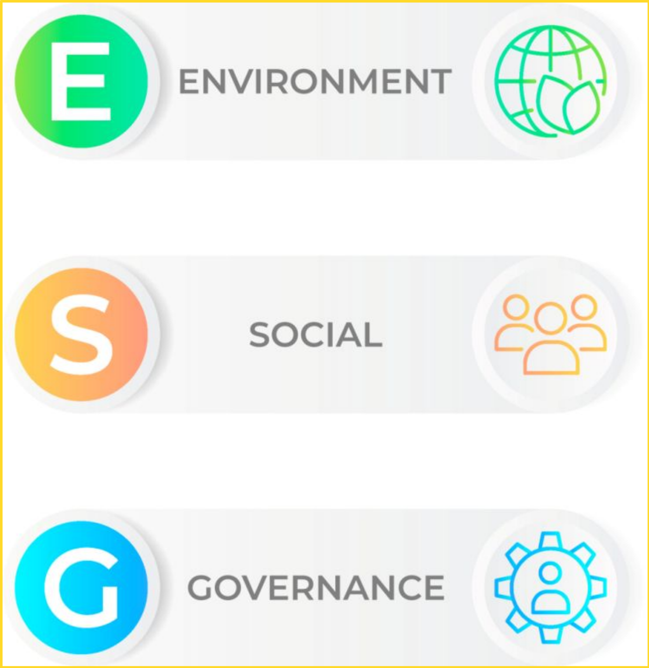
Introduction

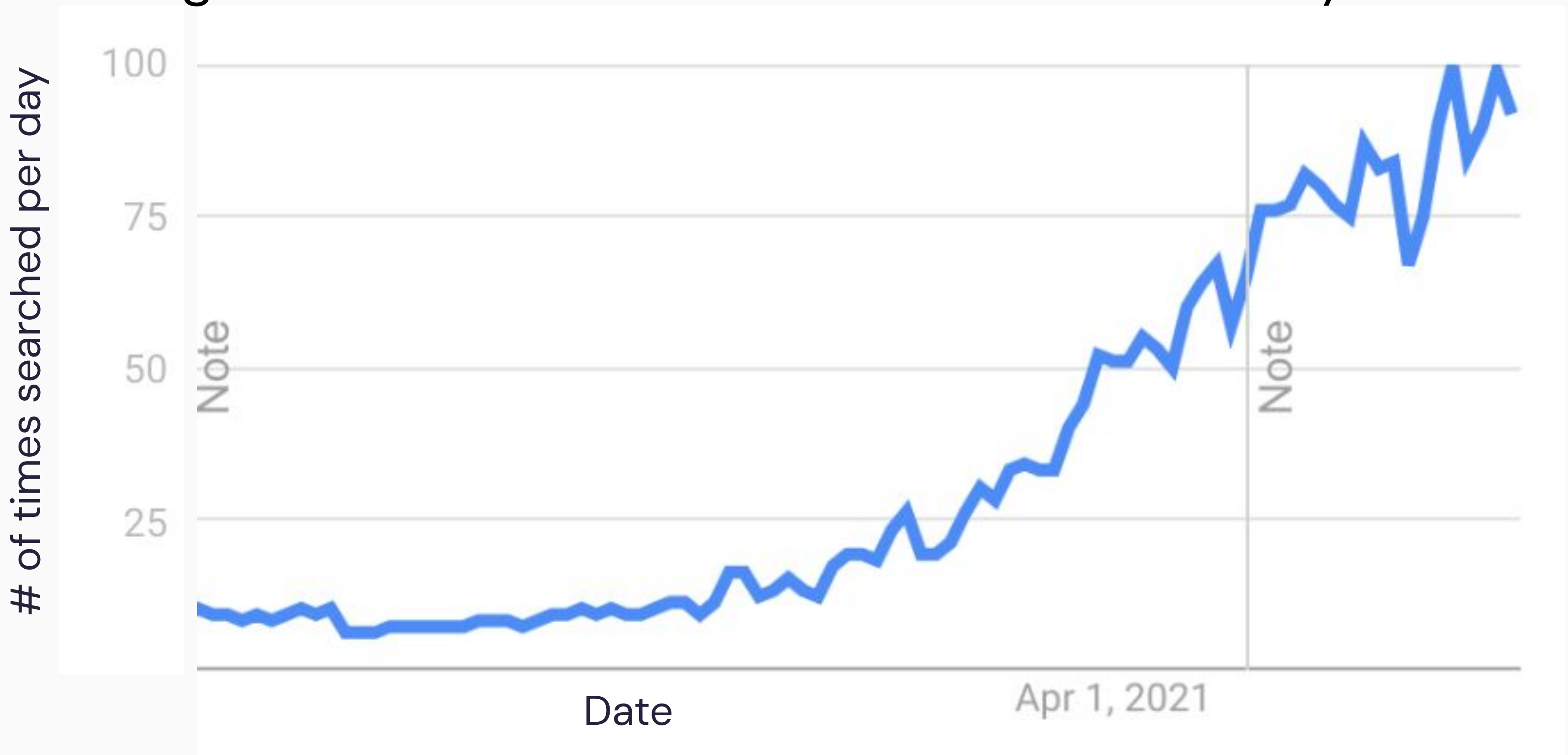
Introduction – ESG Background

What is ESG?

- A comprehensive framework used to assess a company's commitment to sustainability, responsible business practices, and ethical behavior or in the other words Environmental, Social, and Governance performance (ESG)
    - Environmental – greenhouse gas production, waste levels, energy used
    - Social – equality in workspace, support of local environment
    - Governance – corruption in company, company managed properly



Google searches for "ESG" worldwide over last 7 years



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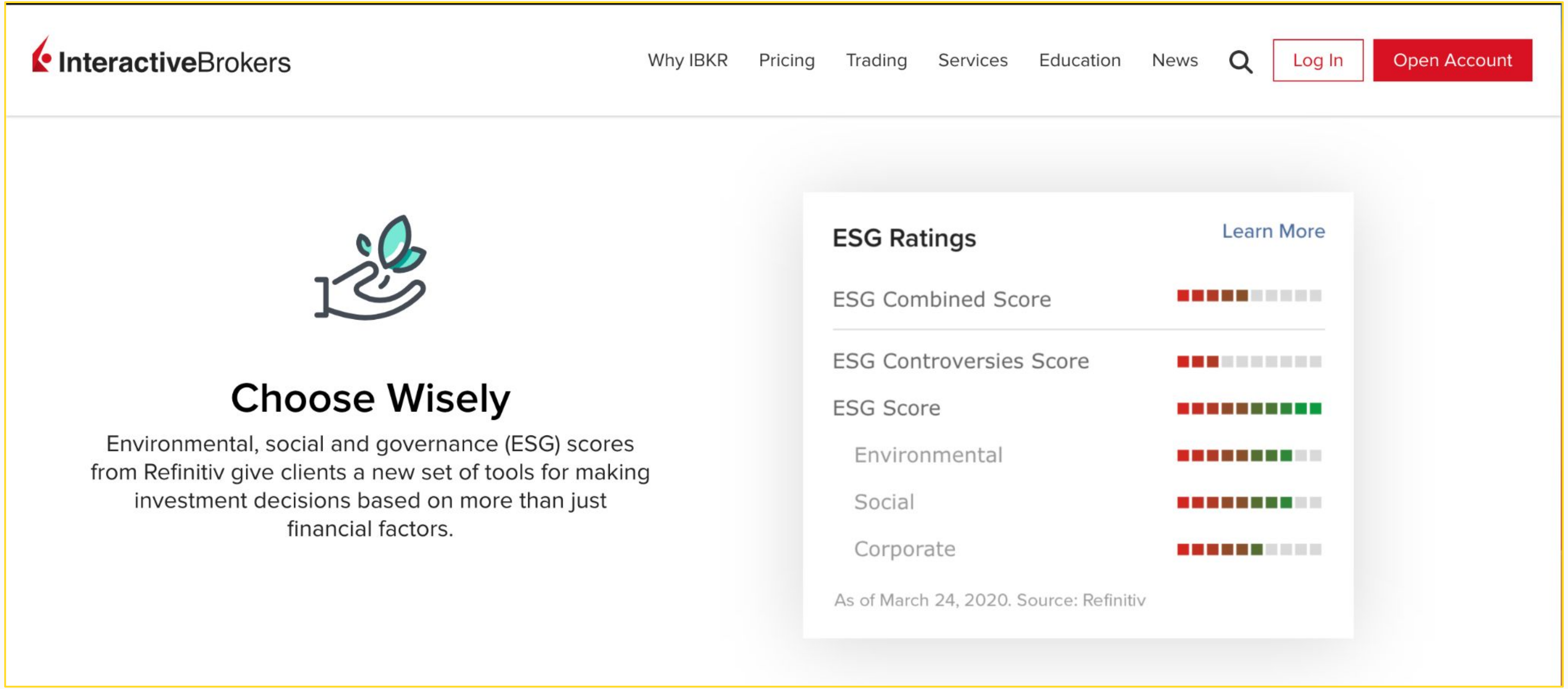
Introduction – ESG Background

What is ESG good for?

Socially conscious investors to screen potential investments.

- Example: Refinitiv ESG company scores



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Introduction – ESG Background

What is ESG good for?

Socially conscious investors to screen potential investments.

Banks to offer more convenient loans

- ČEZ concluded the first loan linked to an ESG sustainability assessment in the amount of CZK 7.5 billion.
    - Date: June 20, 2023

ČEZ concluded the first loan linked to an ESG rating

6/20/2023 11:51 AM, BAACEZ

ČEZ concluded the first loan linked to an ESG sustainability assessment in the amount of CZK 7.5 billion.

Introduction – ESG Background

What is ESG good for?

Socially conscious investors to screen potential investments.
Banks to offer more convenient loans

Non-financial reporting

- Sustainability development has increasingly become a part of non-financial reporting but not mandatory until recently
- As of July 31st, the EC released the final act supplementing Directive of the European Parliament concerning sustainability reporting standards
- ESG reporting is not a legislative dictate but companies are free to determine what they say about themselves


News

EU's New Mandatory ESG Reporting Rules: Don't Miss Your Chance to Comment

Cooley alert

June 16, 2023

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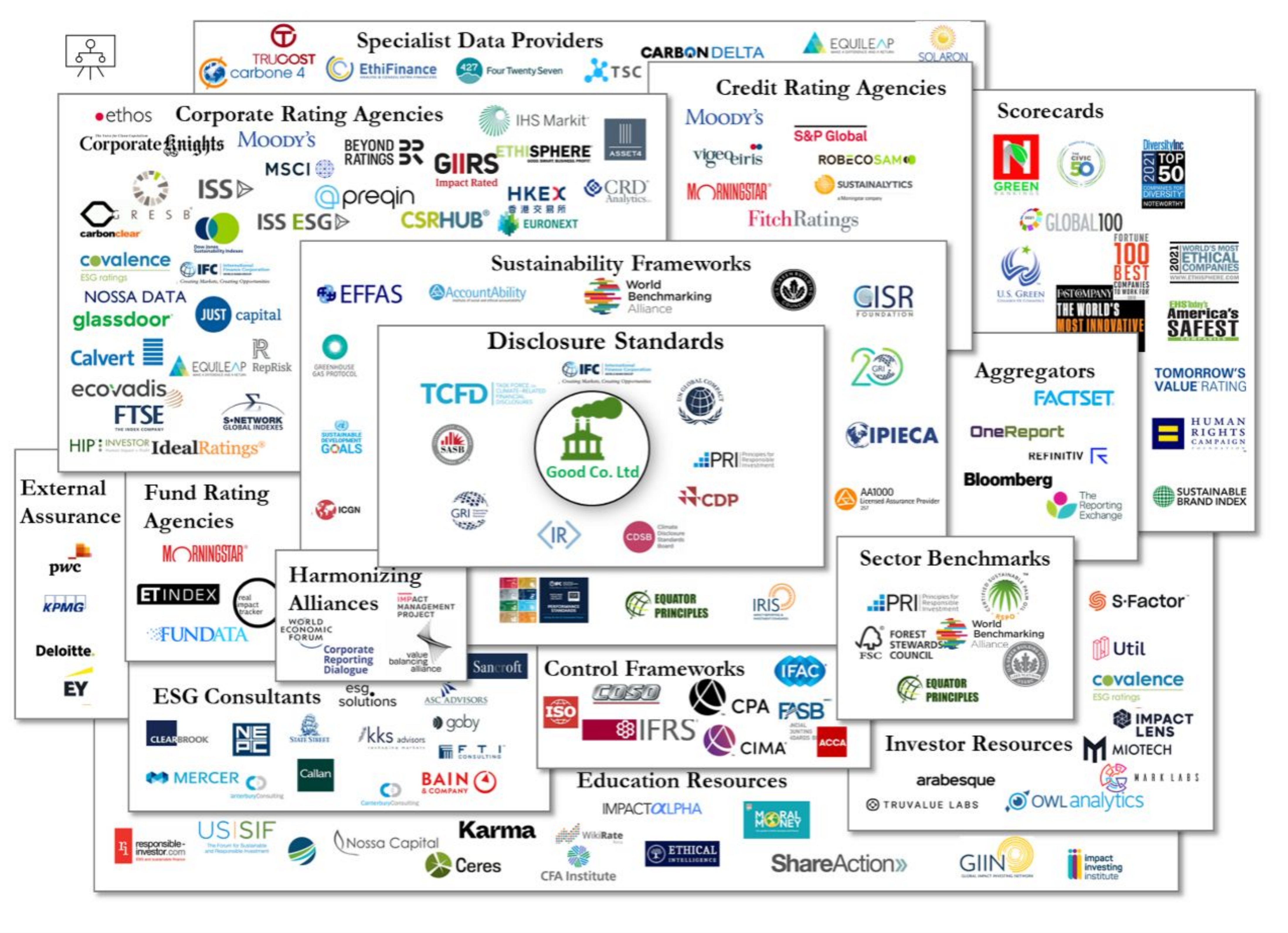
Introduction – ESG Background

ESG Today

- Due to growing need for ESG reporting, there became a need for ways to quantify and classify the ESG performance of companies
- Currently over 1,700 ESG guidelines, 600 frameworks, and 360 standards and regulations regarding ESG



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Introduction - Project Goal

Our Goal was to leverage the daily-collected Semantic Visions data to develop an ESG index, enabling us to assess a company's sustainable development.

Understanding ESG

Categories

Subcategories

“Sub-subcategories”

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Introduction – Understanding

Understanding

ESG

Categories

Environment | **Social** | Governance

Subcategories

"Sub-subcategories"

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Introduction – Understanding

Understanding

ESG

Categories

Environment | **Social** | Governance

Subcategories

Equality, Labor Rights, **Local Support**, Customer Rights

“Sub-subcategories”

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Introduction – Understanding

Understanding

ESG

Categories

Environment

Social

Governance

Subcategories

Equality, Labor Rights, **Local Support**, Customer Rights

"Sub-subcategories"

Community Pro, Startups Pro, Community Welfare, Local Business, Suppliers Pro, Community Contra

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Initial Research

- What do the existing ESG indices look like?
  - Do you need to pay for them?
- What subcategories do these indices use to assess ESG score?
  - What makes up Environmental? Social? Governance?
- What input data do these indices use to create an ESG score?
  - Do other indices use news media? Do they use private company data?
- What is the formula used to calculate an ESG score?
- Do these indices weigh each category (E, S, G) proportionally?
  - Does the number of subcategories matter?
- Is it possible to create an index using purely SV data?

Introduction – Initial Research

Initial Research: Answers

- **What do the existing ESG indices look like?**

- Closely researched 10 of the most popular ESG indices

- Some have company scores available for free, others require subscription
    - 6/10 have scores available for free
        - 4 of these 6 offer a detailed breakdown of the scores for a fee
        - The other two do not offer detailed breakdown

- The indices offer various purposes
    - Investing
    - Lending
    - For the public to understand where companies that they may support stand in terms of their sustainability

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Initial Research: Answers

What do the existing ESG indices look like?

What subcategories do these indices use to assess ESG score?

- Each index breaks E, S, and G into more specific topics for scoring criteria
  - ex. D&B ESG Intelligence
    - Environment: Natural Resources, GHG Emissions & Climate, Environmental Risk, Environmental Opportunities
    - Social: Human Capital, Product & Service, Customer Engagement, Community Engagement
    - Governance: Certifications, Corporate Governance, Corporate Behaviors

- However, each index breaks them down slightly differently
  - Number of subcategories range from 7 (lowest) to 31 (highest)

- We collected the most common and important subcategories of E, S, and G

Initial Research: Answers

What do the existing ESG indices look like?

What subcategories do these indices use to assess ESG score?

What input data do these indices use to create an ESG score?

Combination of various data types

- **Public data**
    - Statistics provided by local government authorities
        - e.g. United States EPA's Greenhouse Gas Reporting Program (GHGRP)
    - Paywalled datasets
        - e.g. Bloomberg ESG data
    - Company disclosure documents
        - Annual reports, Sustainability reports
        - Company policies
    - Media sources
        - News and social media
- **Private ESG assessments**
    - S&P Corporate Sustainability Assessment

Initial Research: Answers

What do the existing ESG indices look like?

What subcategories do these indices use to assess ESG score?

What input data do these indices use to create an ESG score?

Combination of various data types

- **Public data**
  - Statistics provided by local government authorities
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  - Paywalled datasets
    - e.g. Bloomberg ESG data
  - Company disclosure documents
    - Annual reports, Sustainability reports
    - Company policies
  - Media sources
    - News and social media
- **Private ESG assessments**
  - S&P Corporate Sustainability Assessment

To our best knowledge, no other index based solely on media sources

Initial Research: Answers

What do the existing ESG indices look like?
What subcategories do these indices use to assess ESG score?
What input data do these indices use to create an ESG score?

What is the formula used to calculate an ESG score?

- To access the formulas used we need to buy the ESG scores
- We attempted to email index companies but got no responses

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Initial Research: Answers

What do the existing ESG indices look like?
What subcategories did they use to assess ESG score?
What input data did they use to create ESG score?
What is the formula used to calculate an ESG score?

Do these indices weigh each category (E, S, G) proportionally?

- Even ⅓ weight for E, S, and G
- Weight based on number of subcategories under E, S, and G
- Weight based on number of sub-subcategories behind E, S, and G subcategories

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Is it possible to create an index using purely SV data?

Methodology

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STEP 1: Defining Input Data (Subcategories)

Environmental	Social	Governance	Categories

Methodology - Step 1: Defining Input Data

STEP 1: Defining Input Data (Subcategories)

Environmental (5)	**Social** (4)	**Governance** (4)
Greenhouse Gas	Equality	Proper Management
Energy	Local Support	Anti-Corruption
Waste	Labor Rights	Sustainability Efforts
Sustainability	Customer Rights	Political Influence
Biodiversity		

Categories

Subcategories

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STEP 1: Defining Input Data (Subcategories)

Environmental (5)	Social (4)	Governance (4)
Greenhouse Gas (2)	Equality (9)	Proper Management (6)
Energy (2)	Local Support (5)	Anti-Corruption (8)
Waste (12)	Labor Rights (29)	Sustainability Efforts (8)
Sustainability (11)	Customer Rights (3)	Political Influence (9)
Biodiversity (9)		

Categories

Subcategories

(Sub-subcategories)

STEP 1: Defining Input Data (“Sub-subcategories”)

- After our subcategories were created we compared these with the SV’s ESG subcategories using star tree
- We found all of our subcategories to exist in SV and placed all the SV “sub-subcategories” into our new subcategories
    - Example: Equality (Social)
        - 'WORKPLACE_PRO'
        - 'WORKPLACE_DIVERSITY_PRO'
        - 'WORKPLACE_DISCRIMINATION_PRO'
        - 'WOMEN_PRO'
        - 'DIVERSITY_PRO'
        - 'WORKPLACE_DISCRIMINATION_CONTRA'
        - 'WOMEN_CONTRA'
        - 'LAND_CONTRA'
        - 'DIVERSITY_CONTRA'

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Methodology - Step 1: Defining Input Data

STEP 1: Defining Input Data (Missing sub-subcategories)

- Some of our “sub-subcategories” that we used to build our subcategories were not part of ESG in SV data.
- But, we found the missing “sub-subcategories” in other sections of SV data using StarTree.
- We recommend these “sub-subcategories” to be added to the ESG sector of SV data

SV Categories (sub-subcategory)	E/S/G	Subcategory
Best Practices	G	proper management
Business Ethics	G	proper management
Executive Compensation	G	proper management
Quality Management	G	proper management
Corporate Governance	G	proper management
Investor relations	G	political influence
Organizational culture	G	proper management
Pollution control	E	sustainability
Environmental activism	E	sustainability
Sustainable Development	E	sustainability
Lobbying	G	political influence

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Methodology – Step 1: Defining Input Data

Step 1: Data Sources (Elastic vs BQ)

Elastic (threats)

- Pros
  - More articles
  - Weight by Relevance
    - Company relevance > 40
    - ESG relevance > 36
- Cons
  - Less reliable data

BQ (scenarios)

- Pros
  - Reliable data
    - Weighted by scenario score
- Cons
  - Fewer articles
  - Two types of BQ data (Vega and Eden)

Methodology - Step 1: Defining Input Data

Step 1: Reliability of Elastic Data

- We went through 300 articles manually to check if there elastic relevance was accurate
- 100 articles each: APPLE, FOXCONN, SONY
- Filtered by the ESG category relevance average with range 36-70
- Rating System:
  - 1 means zero relation
  - 2 means either company related, esg category related, or weak relevancy (pro/contra wrong)
  - 3 means article fully relates
- Findings:
  - 1 —> 78/300 ~ 26%
  - 2 —> 129/300 ~ 42.5%
  - 3 —> 94/300 ~ 31.5%

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Methodology – Step 1: Defining Input Data

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- Findings:
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  - 2 —> 129/300 ~ 42.5%
  - 3 —> 94/300 ~ 31.5%

Conclusion:
Many threats and companies are falsely assigned to articles due to buzz words throughout webpage.

For example:
Company names being in the suggested articles to read section, not in the actual article

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Methodology - Step 1: Defining Input Data

Step 1: Data Chosen (BQ Vega)

- Elastic data proved to be insufficient for our purposes, so we had no choice but to use BQ data
- For our companies there was much more data in Vega than in Eden and thus we chose to work with the Vega data
    - When comparing the Vega and Eden datasets, we realized that some of the articles in Vega are not in Eden, so we have more data in Vega
- Extracted all ESG related articles for the past year for each of our companies

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Methodology - Step 1: Defining Input Data

Step 1: Data Chosen (BQ Vega)

- Elastic data proved to be insufficient for our purposes, so we had no choice but to use BQ data

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- Extracted all ESG related articles for the past year for each of our companies

Kudos to Bali, Felipe, and Filip for the help

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TOTALLY AWESOME!
Thank you!

Step 2: Equation Designing - Initial Idea

$$I = E(\frac{B_e - D_e}{A_e}) + S(\frac{B_s - D_s}{A_s}) + G(\frac{B_g - D_g}{A_g})$$

$I = ESG\ score$

$E, S, G = category\ weight$

$n = total\ number\ of\ categories$

$n_e = number\ of\ categories\ in\ environment$

$C_j = j^{th}\ subcategory\ in\ respective\ supercategory$

$N_{B,C_j} = number\ of\ beneficial\ articles\ in\ category\ number\ j$

$N_{D,C_j} = number\ of\ detrimental\ articles\ in\ category\ number\ j$

$w_{B,C_J,i} = weight\ of\ i^{th}\ beneficial\ article\ in\ category\ j$

$w_{D,C_j,i} = weight\ of\ i^{th}\ detrimental\ article\ in\ category\ j$

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Step 2: Equation Designing – Questions

- Should each article be weighed the same regardless of how relevant an articles is to the company and category?
- Should E, S, and G each makeup ⅓ of the overall score?

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Step 2: Equation Designing – Solution 1

Should each article be weighed the same regardless of how relevant an articles is to the company and category?

- Used the ‘Score’ metric from BigQuery’s Vega database to help us determine the relevance of an article

- ‘Score’ represents how closely an article relates to the company it is tagged to and the threat that the scenario has
  - On a scale from 0-100

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Methodology – Step 2: Equation Designing

Step 2: Weighed Equation

$$I = ESG\ score$$

$$E, S, G = category\ weight$$

$$n = total\ number\ of\ categories$$

$$n_e = number\ of\ categories\ in\ environment$$

$$C_j = j^{th}\ subcategory\ in\ respective\ supercategory$$

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$$w_{B,C_j,i} = weight\ of\ i^{th}\ beneficial\ article\ in\ category\ j$$

$$w_{D,C_j,i} = weight\ of\ i^{th}\ detrimental\ article\ in\ category\ j$$

Option 1: all subcategories same weight

$$I = \sum_{j=1}^{n} \frac{1}{n} \cdot \frac{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} - \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}}{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} + \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}}$$

Option 2: E,S,G same weight

$$I = \sum_{j=1}^{n_e} \frac{1}{3n_e} \cdot \frac{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} - \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}}{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} + \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}} + \sum_{j=1}^{n_s} \frac{1}{3n_s} \cdot \frac{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} - \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}}{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} + \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}} + \sum_{j=1}^{n_g} \frac{1}{3n_g} \cdot \frac{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} - \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}}{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} + \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}}$$

Step 2: Option 1 vs Option 2

Option 1: $$I = \sum_{j=1}^{n} \frac{1}{n} \cdot \frac{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} - \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}}{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} + \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}}$$

- Pros
  - Each subcategory of E, S, and G is equally important
- Cons
  - E is worth more than S and G. E>S=G

Option 2: $$I = \sum_{j=1}^{n_e} \frac{1}{3n_e} \cdot \frac{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} - \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}}{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} + \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}} + \sum_{j=1}^{n_s} \frac{1}{3n_s} \cdot \frac{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} - \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}}{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} + \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}} + \sum_{j=1}^{n_g} \frac{1}{3n_g} \cdot \frac{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} - \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}}{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} + \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}}$$

- Pros
  - All categories are equal, E=S=G
- Cons
  - The subcategories of E are worth less than the subcategories of G

Step 2: Equation Designing – Solution 2

Should each article be weighed the same regardless of how relevant an articles is to the company and category?

Should E, S, and G each makeup ⅓ of the overall score?

- We decided that it was more important for the main categories (E,S,G) to be equal
- We did this because we thought that if a company had a good rating for only one subcategory of a E,S, or G then the E, S, G rating shouldn't be good because of the lack of variation.
- Example:
    1. company has great reportings on the governance subcategories, but no reportings on the environmental subcategories.

    1. In option 1, this would give the company a great overall rating, however that is not true due to the lack of reporting and knowledge of their environmental performance, while option 2 would give the company a more balanced rating

Step 2: Further Challenges

- Potential negative results
  - Did not account for when there are more detrimental articles than beneficial
    - Results in negative score
- Needed equation to produce results strictly from 0 to 100
  - Normalizing equation

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Methodology – Step 2: Equation Designing

Step 2: Final Equation

- Final Equation:

$$I = \frac{1}{3} \cdot \left(\frac{\sum_{j=1}^{n_e} \frac{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} - \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}}{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} + \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}} + 100}{2} + \frac{\sum_{j=1}^{n_s} \frac{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} - \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}}{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} + \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}} + 100}{2} + \frac{\sum_{j=1}^{n_g} \frac{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} - \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}}{\sum_{i=1}^{N_{B,C_j}} w_{B,C_j,i} + \sum_{i=1}^{N_{D,C_j}} w_{D,C_j,i}} + 100}{2} \right)$$

- Pros
  - Straightforward idea
    - Weighted average of difference between beneficial and detrimental articles of each category
  - Produces results on scale of 0 to 100 that represent the data accurately
- Cons
  - Our normalizing equation is specific to our equation, not standardized

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Methodology - Step 3: Output Designing

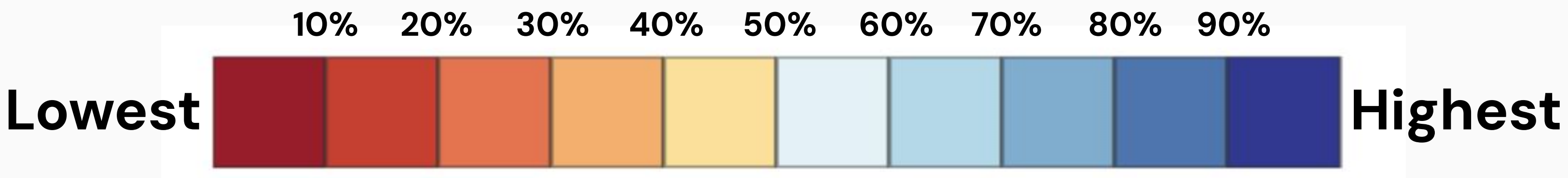
Step 3: Outputs Design

Each output for a company will contain 3 aspects

- Aspect 1: Bubble plot showing total ESG score and category, subcategory, and sub-subcategory breakdown
- Aspect 2: Trend graph that shows ESG scores over a certain period of time as well as the number of articles for each category across this time period
- Aspect 3: A write-up explaining the figures from Aspects 1 and 2 as well as some analysis on the results

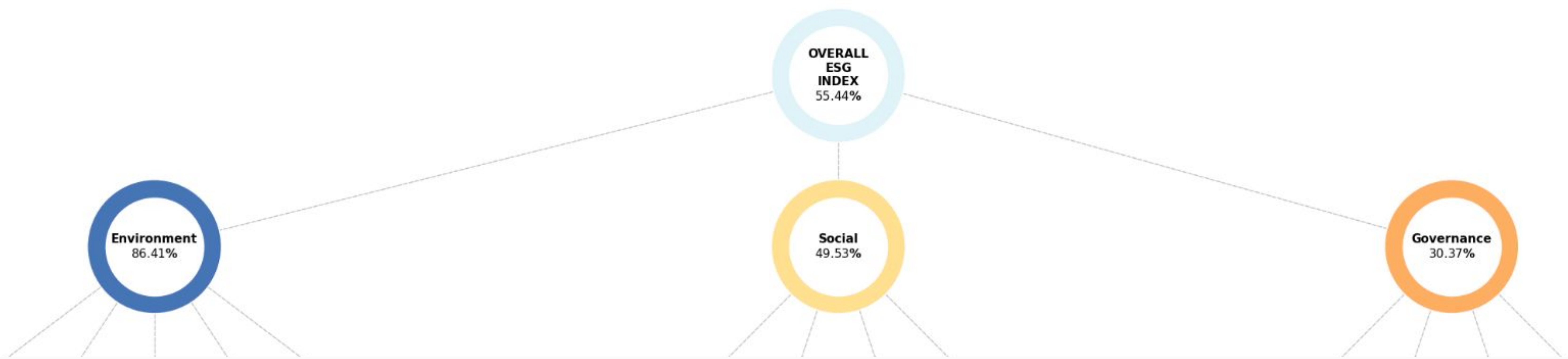
Methodology – Step 3: Output Designing

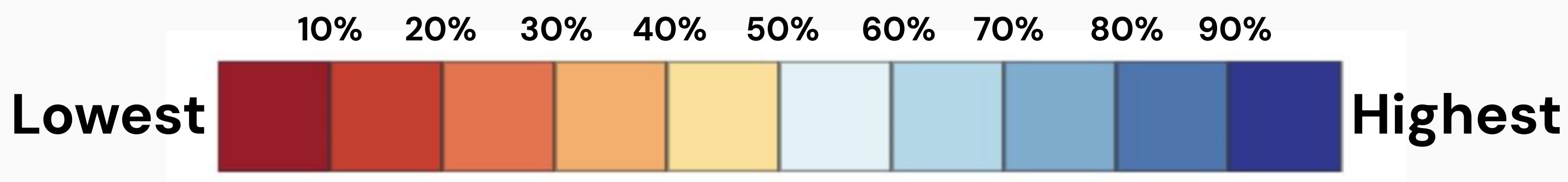
Aspect 1: Overall Bubble Graph



Methodology - Step 3: Output Designing

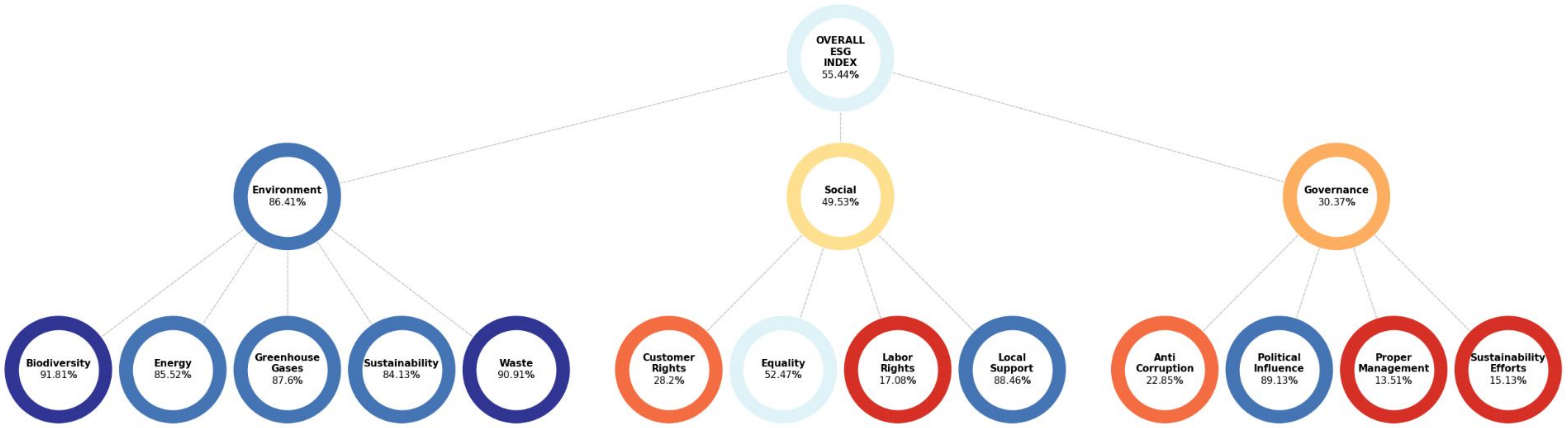
Aspect 1: Category Bubble Graph

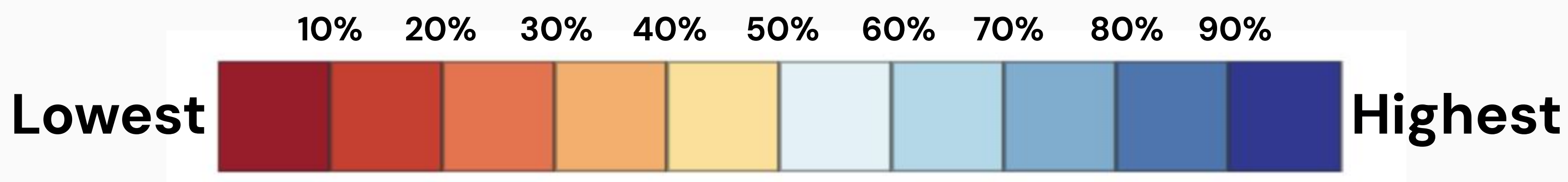




Methodology - Step 3: Output Designing

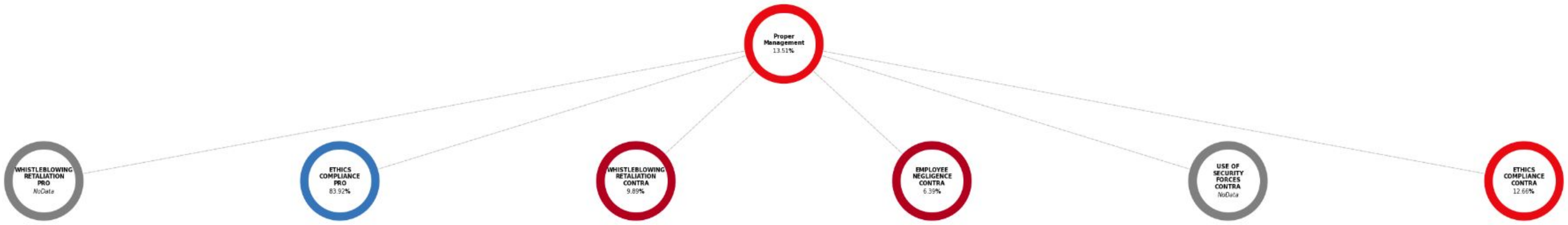
Aspect 1: Subcategory Bubble Graph

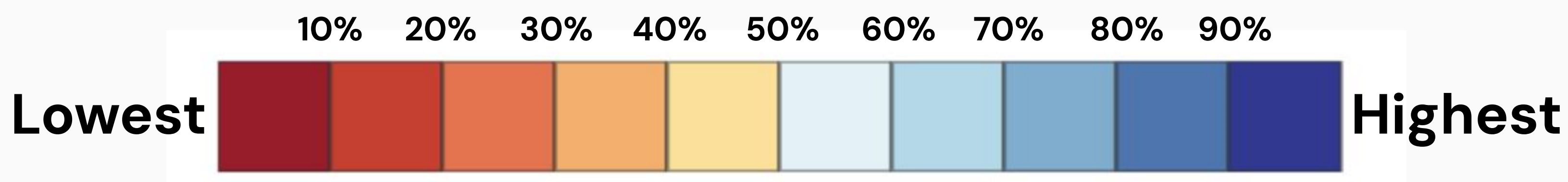




Methodology - Step 3: Output Designing

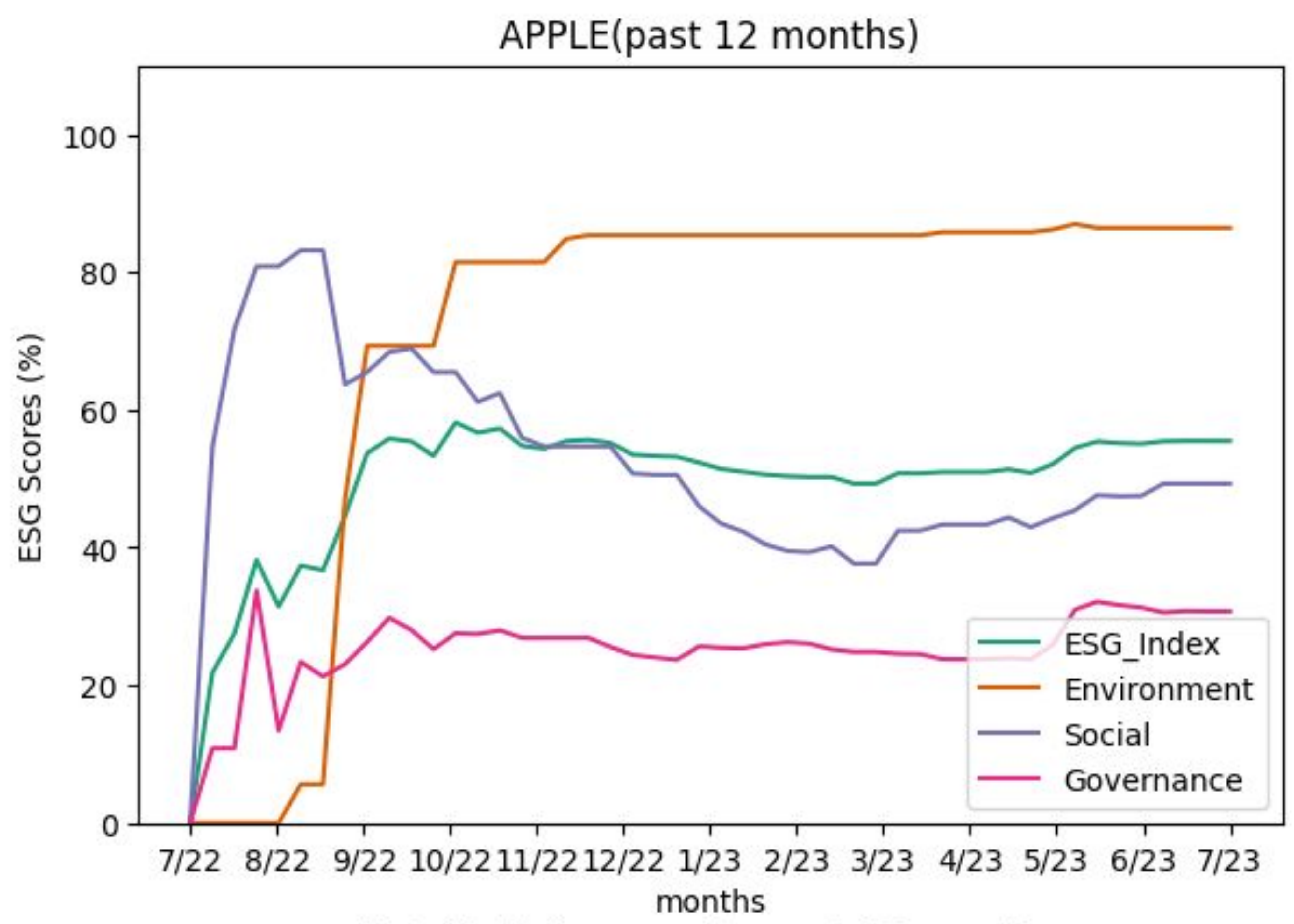
Aspect 1: Sub-subcategory bubble graph

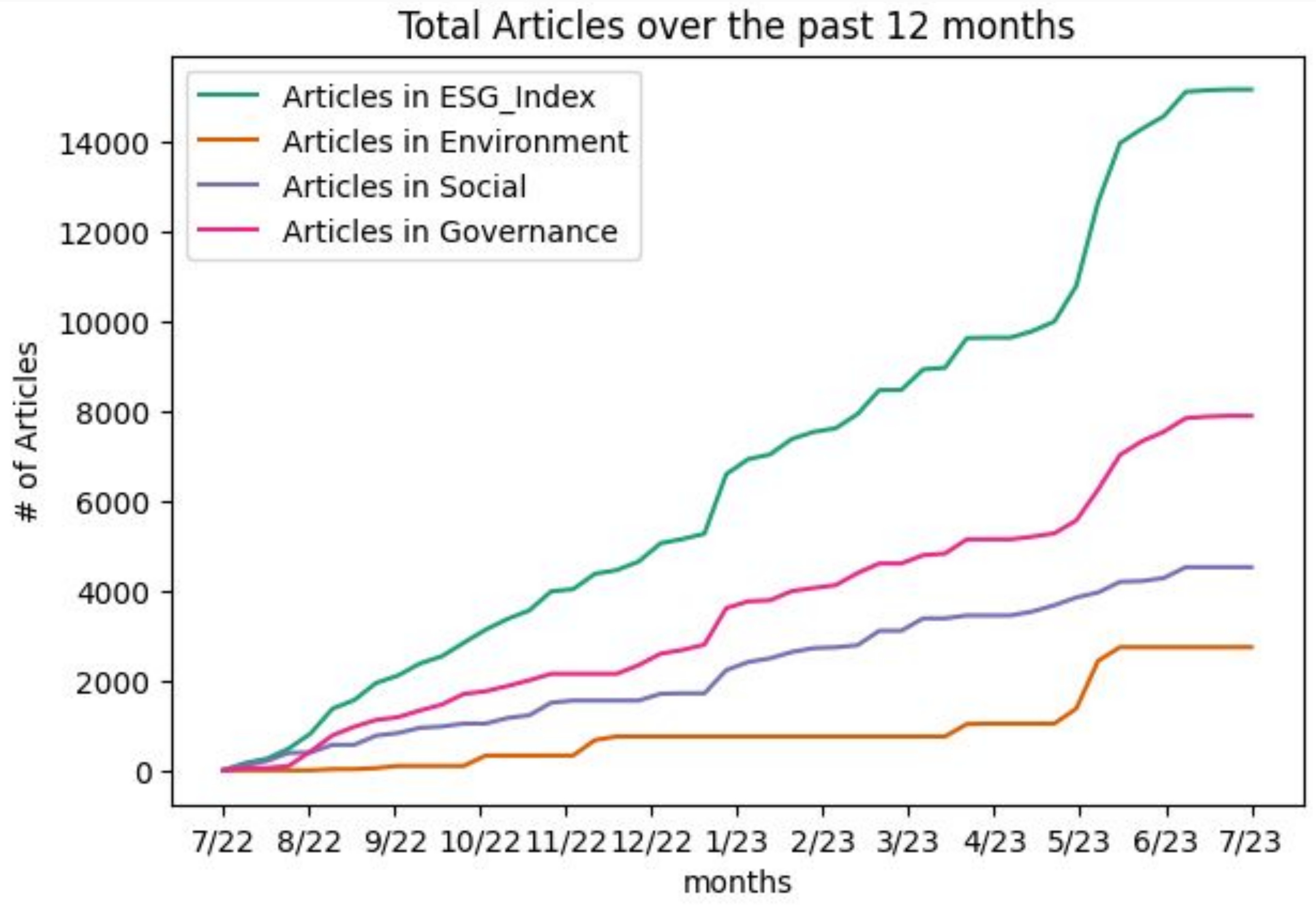




Methodology - Step 3: Output Designing

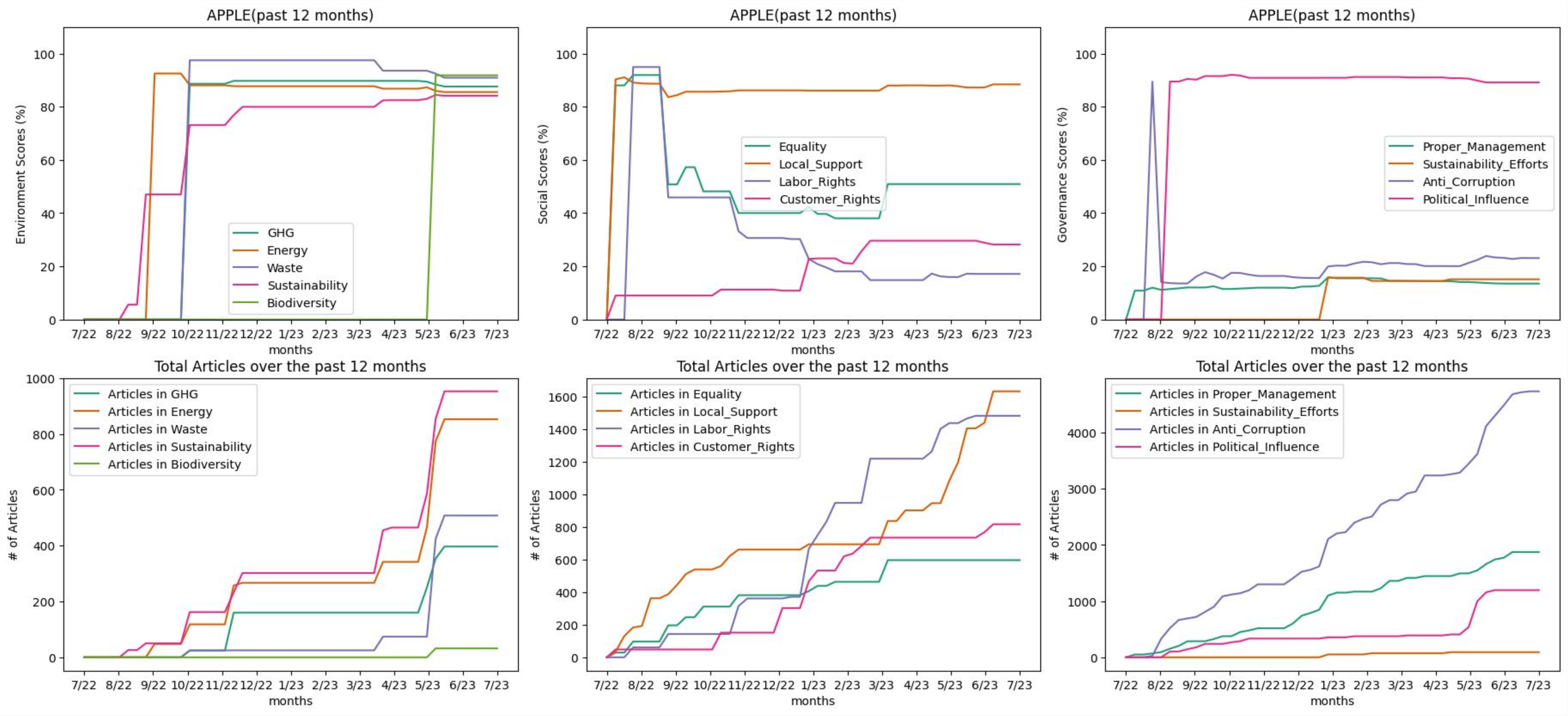
Aspect 2: Trend Graph





Methodology - Step 3: Output Designing

Aspect 2: Subcategory Trend Graphs



Methodology – Step 3: Output Designing

Aspect 3: Example Data Analysis

- Analysis of the different strengths and weaknesses of a company based on the scores given by the bubble graphs
    - Can go into as much detail as necessary since all the numbers from overall scores to sub-subcategory scores are available
- Analyze sudden jumps or drops in ESG score
    - Pinpoint articles and events that cause a boost or drop in the ESG
- Determine which categories have a lack of reporting

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Proof of Concept

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PoC – Choosing Companies

Companies Selection

- We chose the most reported on companies over the last year related to "climate change" in Semantic Visions Search
- Foxconn was also chosen for variation in company industry and size, Julius's wish

1. Amazon
2. Apple
3. Credit Suisse
4. Disney
5. Facebook
6. Foxconn
7. Goldman Sachs
8. Google
9. JP Morgan
10. Microsoft
11. Morgan Stanley
12. Samsung
13. Sony
14. Tesla
15. Walmart
16. Wells Fargo

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PoC - Index Comparison

Overall Values

Company	SV
Samsung	82%
Sony	82%
Morgan Stanley	79%
Microsoft	77%
Disney	75%
Walmart	73%
Wells Fargo	69%
Amazon	68%
Goldman Sachs	68%
Foxconn	66%
Google	64%
JP Morgan	61%
Apple	55%
Credit Suisse	53%
Facebook	53%
Tesla	46%

PoC – Index Comparison

Index Comparison

Company	SV	S&P Global ESG Scores	Sustainalytics	MSCI	Refinitiv
Samsung	82%	38%	61%	64%	82%
Sony	82%	41%	65%	93%	87%
Morgan Stanley	79%	36%	50%	79%	62%
Microsoft	77%	56%	69%	93%	90%
Disney	75%	41%	69%	64%	69%
Walmart	73%	51%	50%	50%	83%
Wells Fargo	69%	31%	36%	36%	75%
Amazon	68%	20%	39%	64%	81%
Goldman Sachs	68%	31%	52%	64%	85%
Foxconn	66%	41%	75%	50%	54%
Google	64%	46%	51%	50%	82%
JP Morgan	61%	34%	41%	64%	83%
Apple	55%	37%	66%	50%	80%
Credit Suisse	53%	na	37%	na	na
Facebook	53%	24%	32%	7%	67%
Tesla	46%	37%	50%	64%	71%

PoC - Index Comparison

Index Comparison

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Microsoft	77%	56%	69%	93%	90%
Disney	75%	41%	69%	64%	69%
Walmart	73%	51%	50%	50%	83%
Wells Fargo	69%	31%	36%	36%	75%
Amazon	68%	20%	39%	64%	81%
Goldman Sachs	68%	31%	52%	64%	85%
Foxconn	66%	41%	75%	50%	54%
Google	64%	46%	51%	50%	82%
JP Morgan	61%	34%	41%	64%	83%
Apple	55%	37%	66%	50%	80%
Credit Suisse	53%	na	37%	na	na
Facebook	53%	24%	32%	7%	67%
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Walmart	73%	51%	50%	50%	83%
Wells Fargo	69%	31%	36%	36%	75%
Amazon	**68%**	**20%**	**39%**	**64%**	**81%**
Goldman Sachs	68%	31%	52%	64%	85%
Foxconn	66%	41%	75%	50%	54%
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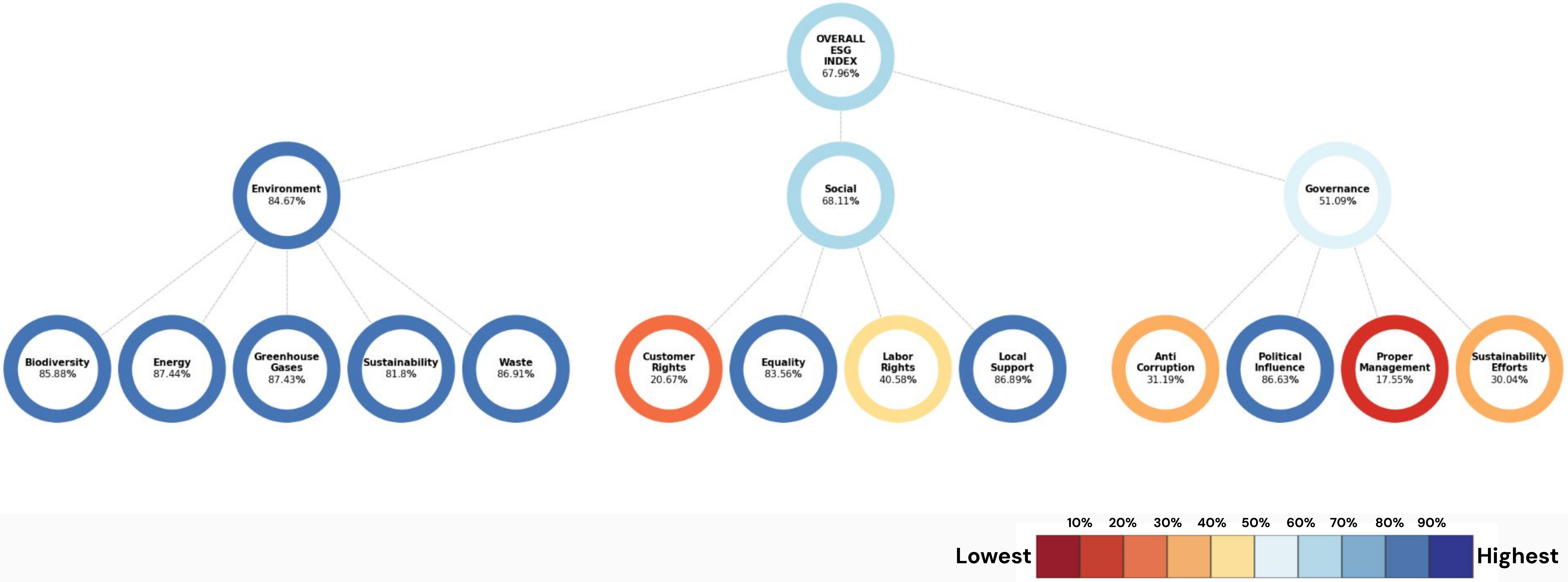
Credit Suisse	53%	na	37%	na	na
Facebook	53%	24%	32%	7%	67%
Tesla	46%	37%	50%	64%	71%

PoC - Output Analysis

Amazon Bubble Graph



PoC – Index Comparison

Index Comparison

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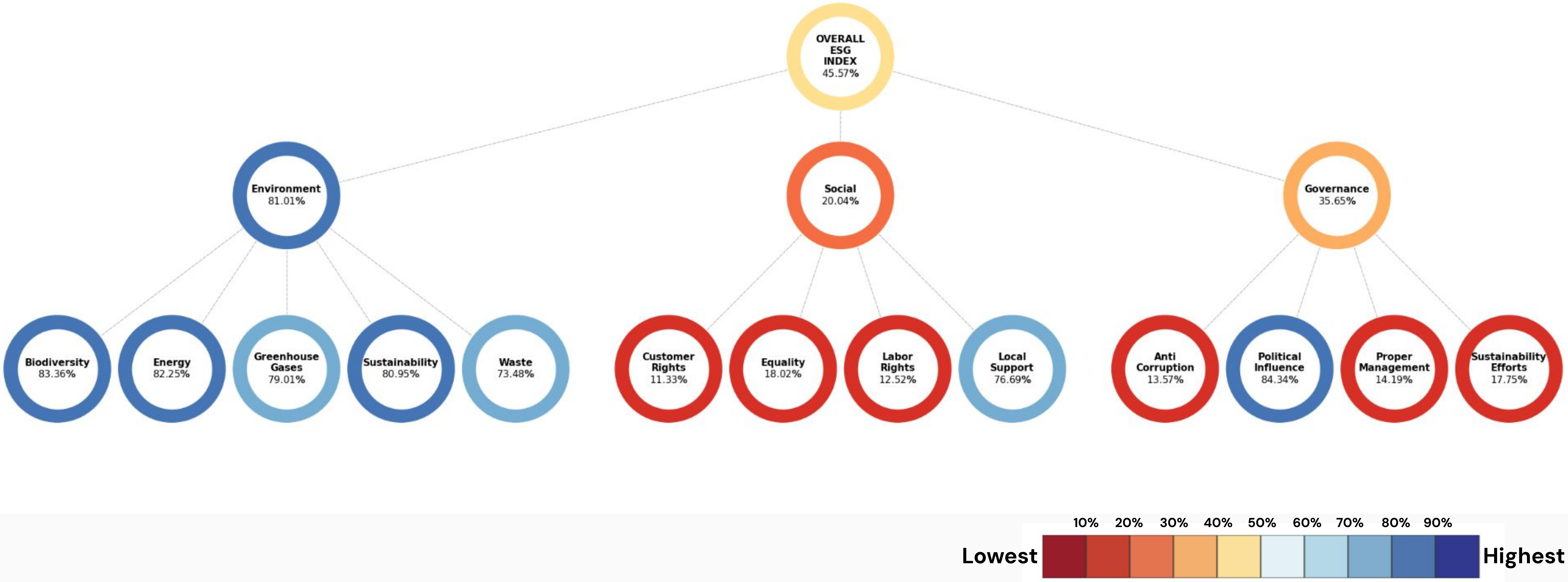
Credit Suisse	53%	na	37%	na	na
Facebook	53%	24%	32%	7%	67%
Tesla	**46%**	**37%**	**50%**	**64%**	**71%**

PoC - Output Analysis

Tesla Bubble Graph



PoC – Index Comparison

Index Comparison

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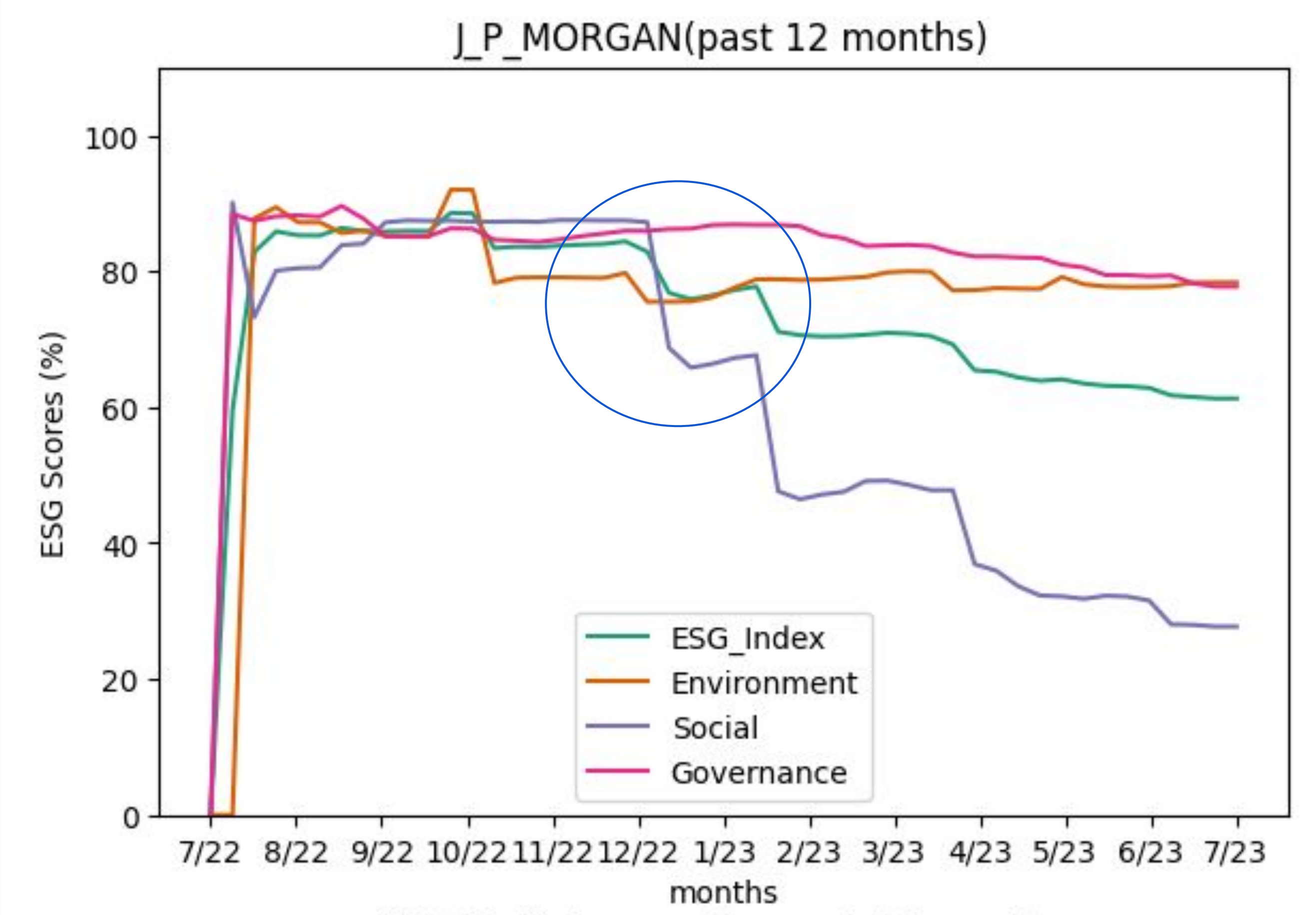
Facebook	53%	24%	32%	7%	67%
Tesla	46%	37%	50%	64%	71%

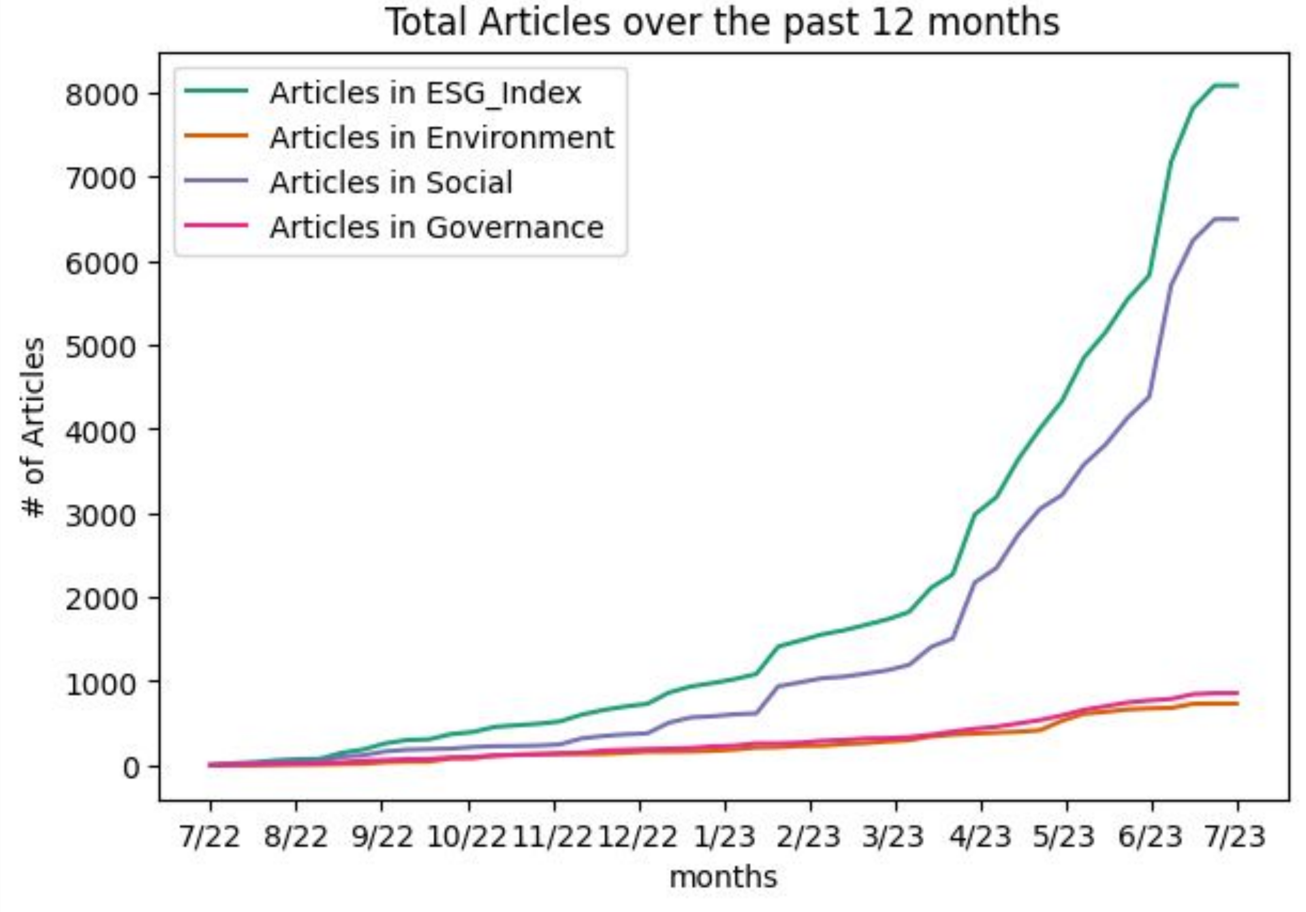
PoC - Output Analysis

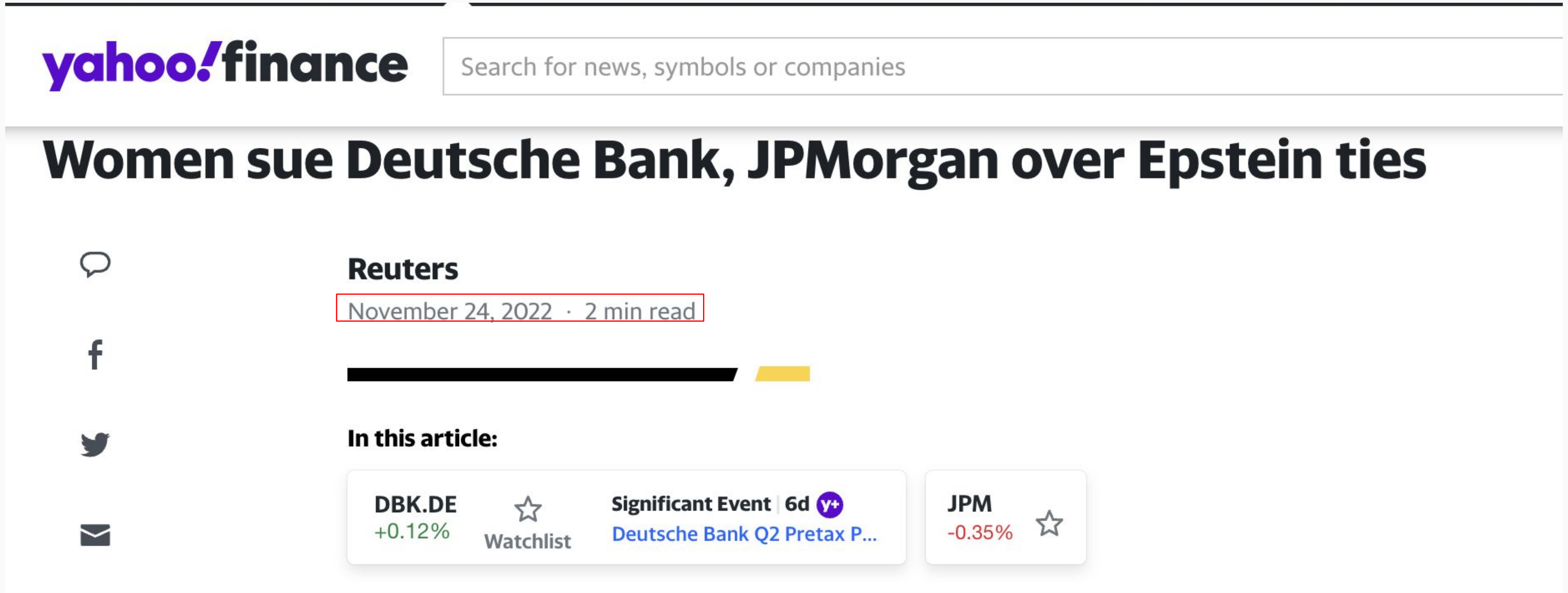
JP Morgan Bubble Graph

PoC – Graphs to Reality

Graphs to Reality







- Epstein victims suing JP and Deutsche bank for enabling and benefitting from abuse and trafficking of young women by Epstein

- Social

SV ESG Index Overview

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Index Overview – Index Summary

SV ESG Index Summary

- Our Index aims to provide in-depth insights, highlighting the specific ESG categories where a company excels in performance, as well as identifying areas that require improvement

- Relying purely on published news articles, our score reflects how the world and the general public perceive a company's sustainable efforts
    - Simulates the average societal perception of a company's ESG
    - Offers a representative view of public sentiment towards the company

- Our niche lies in being the only index, according to our research, that is strictly based on news media

Index Overview – Pros and Cons

SV ESG Index Pros and Cons

Pros

- Real-time Data
- Comprehensive Data Collection
- Detailed Subcategory Breakdown
- Public Perception Insights
- Comprehensive Coverage
- Transparency
- Diverse Sources
- Flexibility
- Public Transparency
- Adaptability to Emerging Issues

Cons

- Data Quality and Reliability
- Limited Data Depth
- Lack of Standardization
- Overemphasis on Negative News
- Lack of Long-Term Perspective
- Subjectivity and Bias
- Incomplete Assessment
- Regulatory and Compliance Issues
- Limited Industry Specific Insights
- PR News Articles

Future Steps

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Future Steps – Improvements

Ways to enhance the ESG Index

Incorporate outside data sources

- We found many websites that carry data on company waste, energy use, pollution, etc.

- All of these websites were paywalled for full data sets
    - Example: PERI (Political Economic Research Institute)
        - Top 100 water pollutant company's data is public
        - Need to pay for rest of companies

- As more mandated ESG reporting legislation gets passed, company ESG data will become more widely available
    - Privately operated ESG databases available by request
        - e.g. Datastream, Eikon, Bloomberg
    - Private companies dedicated to collecting and organizing ESG data
        - e.g. GreenOmeter, Transition Pathway Initiative

- Can pay for this data and use it in combination with news media

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Future Steps – Improvements

Ways to enhance the ESG Index

Incorporate outside data sources

- One of SV's strengths is processing and analyzing large datasets of text
- As the new EC directive goes into effect, more ESG non-financial reporting will become available
- We see this as a great opportunity for SV to apply their pre-existing knowledge and processes to store and analyze ESG related data, and eventually incorporate this data into the ESG index

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Future Steps – Improvements

Ways to enhance the ESG Index

Incorporate outside data sources

Get feedback from clients/consulting companies and eventually incorporate their recommendations

- Offer consulting companies and clients free use in exchange for feedback

Future Steps – Improvements

Ways to enhance the ESG Index

Incorporate outside data sources

Get feedback from clients/consulting companies and eventually incorporate their recommendations

Index Expansion to Cover All Companies in BQ Database

- Currently working with BQ Vega dataset which only has ~4000 companies
- Semantic Visions tracks about 9 million companies in BQ's Eden dataset

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Future Steps – Improvements

Ways to enhance the ESG Index

Incorporate outside data sources
Get feedback from clients/consulting companies and eventually incorporate their recommendations
Index Expansion to Cover All Companies in BQ Database

Percentile rankings

- Rank each company against each other based on our indexes scores
- Gives companies better feel of where they lie compared to peers
- Example of ranking system

Percentile Rankings	Description
96 - 100	Best in class
76 - 95	Above average
26 - 75	Average
6 - 25	Below average
0 - 5	Worst in class

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Future Steps – Improvements

Ways to enhance the ESG Index

Incorporate outside data sources
Get feedback from clients/consulting companies and eventually incorporate their recommendations
Index Expansion to Cover All Companies in BQ Database
Percentile rankings

Providing educational resources

- Create resources explaining the methodology and help interpret the results
- Help clients utilize information to the full potential

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Future Steps – Improvements

Ways to enhance the ESG Index

Incorporate outside data sources
Get feedback from clients/consulting companies and eventually incorporate their recommendations
Index Expansion to Cover All Companies in BQ Database
Percentile rankings
Providing educational resources

Monitoring industry trends and best practices

- Continuously monitor industry trends
- Make index more relevant and effective

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Future Steps – Improvements

Ways to enhance the ESG Index

Incorporate outside data sources
Get feedback from clients/consulting companies and eventually incorporate their recommendations
Index Expansion to Cover All Companies in BQ Database
Percentile rankings
Providing educational resources
Monitoring industry trends and best practices

Pay the interns!

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ESG Index Final Report

- A complete and detailed description of our processes and methodology is available in the “ESG Final Report” document

- Accessible to all who are interested in a step-by-step report on the Semantic Visions ESG Index
    - Contains all relevant sources and files that we created to document our procedures and progress

ESG Index Google Drive

- All files and documents that we created and worked on are available in Google Drive

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Acknowledgements

- Julius
- Anna
- Felipe
- Filip
- Bali
- Gabriela

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