EcoScore: Automated ESG Scores for the Fashion Industry

1st Sophia Africk
Dept. of Electrical and Systems Engineering
University of Pennsylvania
Philadelphia, PA
safrick@seas.upenn.edu

2nd Skylar Ronkin
Dept. of Computer and Information Science
University of Pennsylvania
Philadelphia, PA
sronkin@seas.upenn.edu

3rd Margo Squire
Dept. of Electrical and Systems Engineering
University of Pennsylvania
Philadelphia, PA
squirem@seas.upenn.edu

4th Mira Zutshi
Dept. of Electrical and Systems Engineering
University of Pennsylvania
Philadelphia, PA
mzutshi@seas.upenn.edu

***Abstract*—Environment, Social, and Governance (ESG) issues are widespread within the fashion industry, indicating the need for a concise ESG metric to explain sustainability in apparel supply chains. However, current ESG metrics are created manually at the company level, and are frequently subject to bias and misrepresentation. ecoScore uses unsupervised machine learning and regression models to assign reliable, relative ESG scores to suppliers in the fashion industry. Using a subset of suppliers from a dataset provided by the company Sourcing Playground, we first pre-process data to examine features including specific ESG criteria satisfied by each supplier. Then, we use Factor Analysis of Mixed Data (FAMD) to reduce dimensionality, while continuing to capture a significant portion of the variance in the data. The resulting transformed data is clustered using *k-means* clustering to further analyze and understand patterns in the data. We then compare the total number of certifications for a supplier to the transformed data points to create a scoring rule; a quadratic equation is fit to the data using ordinary least square regression to optimize. To further verify our approach and prove replicability, we assign scores to suppliers from a validation set. The result allows our complete model to assign each supplier a concise, comprehensive ESG score on a 0-100 scale, and these supplier scores are relative rather than absolute. The use of unsupervised machine learning and regression allows us to create an automated methodology for assigning apparel suppliers numerical ESG scores – a unique deliverable for Sourcing Playground.**

***Index Terms*—sustainability, ESG, unsupervised learning, fashion industry, supply chain**

I. Introduction

THE fashion industry accounts for 10% of global carbon emissions and 20% of global plastic production; labor violations are rampant, with forced and child labor employed in many factories [1]. Such environmental, social, and governance (ESG) risks in the fashion supply chain are of growing concern to many stakeholders. Fashion companies increasingly review and analyze their supply chains in order to meet the standards they have promised consumers. Investors leverage ESG data to determine potential sustainability risks in targets' operations. As a result, demand for accurate, comprehensive, and concise ESG scoring in the fashion industry is rapidly rising.

Funded by the Department of Electrical and Systems Engineering at the University of Pennsylvania, School of Engineering and Applied Science

A. Existing Solutions

Currently, it is difficult to hold fashion companies accountable for ESG metrics because of the lack of cohesive data regarding their supply chains, extreme bias and misrepresentation within scoring, and a failure to analyze the root of sustainability issues at the supplier level.

In the fashion industry, most efforts in ESG scoring at the supplier level are biased and inefficient. ESG metrics are typically presented by individual suppliers (used interchangeably with 'factories' hereinafter), which conduct internal self-assessments of their own practices. The resulting ESG reports are unreliable and difficult to compare across suppliers, as there is no standard reporting process. Typically, these results are also not numeric, and simply provide a qualitative assessment of their operations. Any insights from these reviews are calculated manually, which makes them difficult to automate and scale. To better understand supplier ESG practices within the context of the overall industry, there must be a holistic numerical scoring methodology, conducted externally to decrease bias and enhance comparability.

There have been several efforts to build an external scoring model by major agencies, including KLD, Sustainalytics, Moody's ESG (Vigeo-Eiris), S&P Global (RobecoSAM), Refinitiv (Asset4) and MSCI [2]. However, these efforts mostly exist at the broader company level. The models and any calculated metrics, therefore, do not include inputs at the supplier level, where most companies' activities actually take place. Additionally, there is clear divergence in the ESG ratings from independent agencies; across these agencies, the correlation between scores for the same company ranges from

0.38 to 0.71 due to variations in the scope, weighting, and sourcing of raw data [3].

B. Proposed Solution

The creation of a comprehensive, quantitative ESG scoring model for suppliers is nontrivial and challenging in nature. Since there is no reliable score to compare results against, and the data points are unlabeled, we must rely on unsupervised learning models that are able to process both categorical and quantitative data types. In addition, current unsupervised learning models alone are not able to output simple, ranked scoring metrics to solve this problem. Therefore, a combination of unsupervised machine learning and regression models must be utilized to create ESG scores.

In this project, we aim to develop a scoring methodology that is concise, holistic, and numerical in nature to address the issue of sustainability in fashion industry supply chains. We apply dimensionality reduction and unsupervised learning methods to our initial dataset and incorporate the output into an optimization model, which compares the transformed data to an optimal metric to produce a score. Using this methodology, we assign scores to a validation set of suppliers to further verify our approach and prove replicability. The resulting scores on a 0-100 relative scale are simple for stakeholders to interpret and compare.

C. Stakeholders and Value Proposition

As we work to develop a strong ESG scoring model, we hope to impact the following distinct stakeholders:

1) *Fashion Companies*: Fashion companies' sourcing teams need transparency into their supply chains in order to meet regulatory requirements, ease their ESG reporting process, and maintain respect from the public and investors. ecoScore's platform would help these companies understand whether they are meeting their internal ESG goals, as well as pinpoint where to alter their supply chains if their goals are not currently met. By providing a single score using the same model for all suppliers, ecoScore allows companies to easily compare a wide range of factories, while also filtering by areas such as location, or types of products produced. Additionally, ecoScore is trained on publicly available U.S. import data and verified supplier certifications, so it is generally more reliable than companies' internal research.
2) *Investors*: Investors want to understand the supply chains of current holdings and potential targets because ESG risks and resulting public scandals can lead to great financial loss. In fact, ESG-conscious investing has been shown to be correlated with higher equity returns and reduced downside risk [4]. With ecoScore, investors are able to search for a company and understand its average supplier score, which can act as a proxy for overall ESG practices; for further research, they can examine more detailed individual supplier scores for that company, which may point to areas of risk or potential improvement.
3) *Consumers*: According to a report published in January 2022 by First Insight and the Wharton School's Baker Retailing Center, two thirds of consumers said they would pay higher prices for sustainable goods [5]. By making part of the ecoScore solution (for example, a company's average supplier score) available to the public, consumers would increasingly be able to hold companies accountable for their sustainability practices. This may encourage them to make changes in their supply chains to improve their average supplier-based score.
4) *Factories*: While suppliers are not directly involved in our ESG score creation, they are the subject of our ratings. If ecoScore becomes standard in the industry, factories could try to influence the scoring and misrepresent statistics and certifications, so it is important that they remain a third party.

Key Contributions. We apply machine learning models to this problem in order to design a standard methodology for ESG scoring that is both verified and unbiased. Once trained on initial data, the model output of the test set shows a clear alignment with the initial results, proving that our model can reliably and precisely calculate supplier ESG scores. The resulting relative supplier scores will create a standard that allows stakeholders to compare suppliers across countries and product types. This will be a key advancement towards achieving transparency and accountability regarding ESG practices within the fashion industry.

II. Data

The data used to develop ecoScore is significant in a few factors: its subject, its source, and its increased reliability. This differs from many other available datasets within the fashion industry. First, this is supplier-level data, meaning information and features pertain to a given factory. This differs from standard datasets, which focus on broader data for companies that are consumer-facing firms within the fashion industry (e.g. Adidas, Target, etc.). Second, our supplier-level dataset originates from publicly available import and export data, scraped from multiple sources and joined together to combine features from the same factories. Because the data is publicly available, as opposed to data provided by the factory itself, there are fewer biases and doubts about the accuracy of the data due to its sources. Finally, another unique element of reliability is the certification aspect of the dataset. This data includes verified certifications from external agencies, which confirm certain criteria to which a given factory adheres. Each of these three factors led to our usage of the dataset, as it lends itself to more reliable results based on public information and external diligence, as compared to biased data sourced from factories themselves.

A. Dataset

The dataset used to develop ESG scores for suppliers within the fashion industry is provided by Sourcing Playground, a UK-based startup dedicated to accumulating public data on fashion companies and their suppliers and providing both quantitative and qualitative insight to inform companies of their own ESG practices. While there is data on hundreds of thousands of suppliers, we randomly selected 5000 data points on which to train our model; the methodology from developing a score on this subset of the data can then be applied to the full dataset to assign ESG scores to all known suppliers.

There are two stipulations in randomly selecting the data points. First, we only select suppliers that produce products from a pre-determined set of categories that encompass a large portion of fashion related products. This includes coats, denim, dresses, shirts, sweaters, trousers, and t-shirts. Second, we only select suppliers with at least one verified certification, as it is nearly impossible to rate factories that have not been awarded any certifcation. These certifications and their relevance are explained further in Section II-B.

B. Features

The original dataset has a highly nested set of features. For each supplier, which aligns with one row in the dataset, features include:

1) The name of the supplier
2) The total weight of product the supplier produces
3) A nested list of the supplier's clients
4) A nested list of product types that the supplier produces (t-shirts, denim, dresses, etc.)
5) A nested list of countries where the supplier has factories
6) A nested list of certifications the supplier has

Each certification within the nested list is awarded to a supplier by an external regulatory agency. These agencies check for a series of predetermined criteria and subsequently provide a certification based on fulfillment of said criteria. From the original dataset, there are three main categories in which these certifications fall: ethical and labor, sustainability, and verification. From this information, it is clear that the certifications cover each aspect of ESG (environment, social, and governance factors) and therefore will inform our comprehensive ESG scoring methodology.

C. Data Pre-Processing

To prepare our dataset to be an adequate input for our model, we pre-process the features to fit a dataframe (table) format. To flatten the features with nested list values, we either extract individual values from those lists or one-hot encode values, depending on the feature. For the "Country" feature – the nested list of countries in which a supplier manufactures – we select only the single most common country from a supplier's list for our model analysis. A supplier having multiple country locations is an outlier in the dataset, and in those rare cases, the second country is significantly less frequent in production quantity. For the "Product" feature, we first group all products into broader categories, such as the new category *coat* encompassing 'trench coat,' 'raincoat', and 'coat,' among other related product types from the original list. Then, the most common category for each supplier is selected as the main product for the model.

TABLE I: Pre-Processed Data Fields.

#	Column	Dtype
0	totalWeight	int64
1	country	String
2	product	String
3	la_gender_equality	bool
4	en_conserve_water	bool
5	en_zdhc	bool
6	en_carbon_emission	bool
7	la_health_safety	bool
8	la_freedom_association	bool
9	la_living_wage	bool
10	la_training_procedure	bool
11	la_no_child_labour	bool
12	la_no_forced_labour	bool
13	la_wellbeing_programs	bool
14	la_wider_community	bool
15	ma_protect_rights_raw_materials	bool
16	la_social_procedures	bool
17	en_reduce_waste	bool
18	en_reduce_landfill	bool
19	en_no_harmful_chemical	bool
20	en_no_harmful_techniques	bool
21	en_recycled_product_20	bool
22	en_product_can_be_recycled	bool
23	ma_sustainably_sourced	bool
24	ma_respect_animal_rights	bool
25	tr_product_traceable	bool

Finally, in terms of certifications, we identify the specific, required criteria necessary for a supplier to be awarded each given certification. This process is conducted for each of the 39 certifications to obtain a list of 23 individual criteria. Since some certifications have similar required criteria, we account for any overlap for each supplier when creating these new features. In conducting this analysis, we are able to break down a supplier's list of awarded certifications into a binary variable of *True* or *False* for each individual ESG-related criteria. This gives the final feature set of ESG criteria, as seen in Table I.

Using this feature set, we then conduct dimensionality reduction, as described in III-A, to develop our scores.

III. Methodology

Implementing an ESG scoring methodology that outputs a numerical value is challenging when working with data that is both categorical and quantitative in nature. In addition, our dataset has no labels, preventing us from using supervised learning methods. For these reasons, we must rely on unsupervised machine learning to create supplier ESG scores. We find that the best unsupervised methodology employs both dimensionality reduction, using Factor Analysis of Mixed Data (FAMD) and clustering to find clear patterns in the data. To create a numerical score output for unlabeled data, identifying these patterns is critical. After conducting these steps, we design an optimization function to output the actual score. In this section, we detail the steps taken to create these scores;

in section IV, our results confirm the effectiveness of this methodology.

A. Dimensionality Reduction (FAMD)

Dimensionality reduction is a common technique in unsupervised machine learning used to identify previously unknown patterns within the dataset. This occurs through the transformation of data from a high-dimensional space to a low-dimensional space. In this transformation process, the low-dimensional representation of the data maintains the most important "information," or properties from the original dataset, separating signal from noise. It does this by transforming the data into new components that represent a combination of features responsible for the most variance in the data. We can then select the most influential components to reduce the dimension of the dataset. Once in this transformed space, the data can be more easily interpreted and more clearly visualized because of its lower dimension.

Because the dataset we work with is high-dimensional and is both quantitative and categorical, we choose to work with a dimensionality reduction technique called Factor Analysis of Mixed Data (FAMD). FAMD is used specifically on datasets with mixed quantitative and categorical features. It uses a combination of Principal Component Analysis (PCA) on quantitative features, and Multiple Correspondence Analysis (MCA) on categorical features to capture the variance in the data in a lower dimensional space.

We input the pre-processed dataset into a standard FAMD model found in the `Prince` Python package.

B. K-means Clustering on Transformed Data

To analyze the FAMD output and identify patterns in the data points in a lower dimensional space, a *k-means* clustering model is fit on the first four components of each transformed data point. To determine the optimal number of clusters, a combination of the elbow method and the silhouette method are used. The elbow method analyzes the trade-off between inertia and number of clusters; the silhouette method assigns a "silhouette score" to each data point in a cluster to compare how close it is to its assigned centroid compared to other centroids.

Clustering on the transformed data creates groups of similar data points based on the data's original features. This helps give insight into any notable similarities among the clusters, particularly related to certification criteria; thus, while the clustering results (i.e., which cluster a given data point belongs to) are not directly input into the scoring system, they help inform the transformation of the FAMD results into a numerical score from 0-100.

We input the first 4 transformed principal components from the FAMD model into a *k-means* model from the `sklearn` Python package.

C. Score Development

In order to create a score, we first assign each factory's total number of certifications (distinct from the unpacked

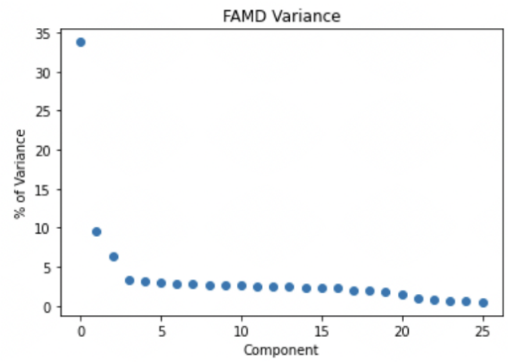

Fig. 1: Contribution of FAMD components to variance in data

certification criteria we use as input) as its label. We then fit a regression model with this label as output and the first two principal components from FAMD as input. We use only the first two principal components based on results in IV-A, which show that these components capture a significant portion of the variance in our data (seen in Figure 1). Using the optimal coefficients from this regression model, we plug in each factory's first two components to get its score. Finally, we rescale the scores so they range from 0-100.

We use the Ordinary Lease Squares method from the `statsmodel` Python package to regress and optimize for coefficients to determine scores.

IV. Results

A. Dimensionality Reduction (FAMD)

Fitting FAMD with 26 components to our 5000 training data points yielded the results in Table II.

The first transformed component accounts for 33.80% of variance in the data and the first four components cumulatively account for more than half of the variance (Figure 1). Thus, FAMD is successful in capturing the variance between factories, which helps differentiate their relative scoring, in a significantly lower dimensional space.

Based on these results, we choose to move forward with the first two transformed components, capturing 43.45% of the variance in the data, since the additional components only add marginal information. Additionally, using just two components allows us to interpret the results more easily, which is critical for models that are used in applied industry settings.

TABLE II: FAMD Output

FAMD Eigenvalues 1 - 4			
Number	Eigenvalue	Explained Variance	Cumulative Explained Variance
1	160.880	33.80%	33.80%
2	45.947	9.65%	43.45%
3	30.399	6.39%	49.84%
4	16.126	3.39%	53.23%

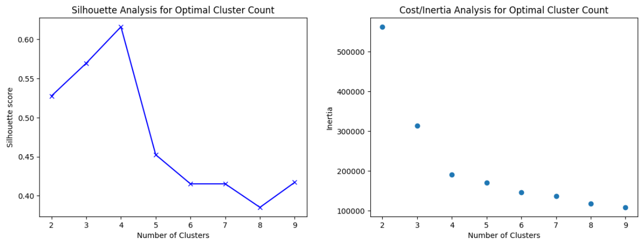

Fig. 2: Determining optimal cluster count with silhouette scores (left) and inertia (right)

FAMD also helps reveal which certification criteria might be most important for differentiating between good vs. bad factories. Some of the criteria that most significantly contribute to the first reduced component are la_gender_equality, la_no_child_labour, la_no_forced_labour, and la_training_procedure.

B. K-means Clustering on Transformed Data

The optimal number of clusters is four, based on our results from both the elbow and silhouette methods (Figure 2).

Clustering on the transformed data allows us to identify four distinct groups, with each cluster of factories aligning to a different range of certification criteria. Of the four clusters, factories in Cluster 3 have the highest average number of certification criteria fulfilled, followed by Cluster 2, Cluster 1, and Cluster 0 with the lowest average number of certification criteria fulfilled. For certain certification criteria in the "better" clusters, all of the factories have obtained that criteria, while other clusters contain zero factories with that same criteria satisfied; this further indicates a clear divide between the clusters. The sizes of the clusters vary from 607 to 2190 out of the total of 5000 factories analyzed.

We visualize these clusters in Figure 3 with the first and second components of the FAMD transformed factory data. These two components, as discussed, capture 43.45% of the variance. The clusters, paired with an optimization function based on additional factors, help to inform the basis for a numerical ESG score from 0-100.

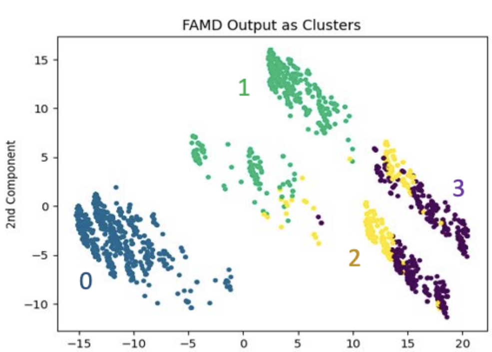

Fig. 3: Cluster results from FAMD output

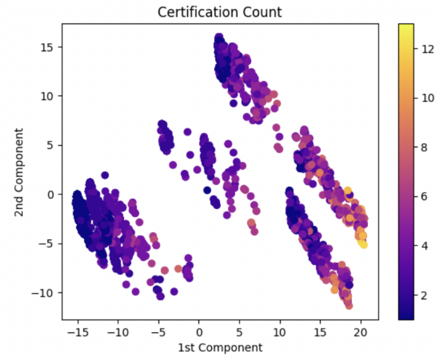

Fig. 4: Certification count mapped onto first two components

C. Scores

Using the original set of features, we compute the total number of certifications for each factory. In Figure 4, we see that the suppliers with more certifications (in yellow) all have similar coordinates in the two dimensional space, so we fit a regression with the first two principal components as input and the number of certifications as the label (σ).

We define our score as:

$$\alpha_1 x + \alpha_2 x^2 + \beta y + b$$

and using ordinary least squares regression, we optimize the following expression:

$$argmin_{\alpha_1,\alpha_2,\beta,b} \sum (\alpha_1 x + \alpha_2 x^2 + \beta y + b - \sigma)^2$$

The following coefficients are all significant:

$$\alpha_1 = 0.0857$$

$$\alpha_2 = 0.0064$$

$$\beta = 0.0213$$

$$b = 1.5866$$

We examine the distribution of the scores between 0 and 100 and see that they are concentrated on the lower end of that scale, as seen in Figure 5.

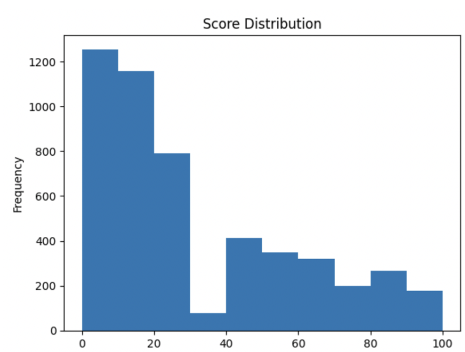

Fig. 5: Distribution of supplier scores

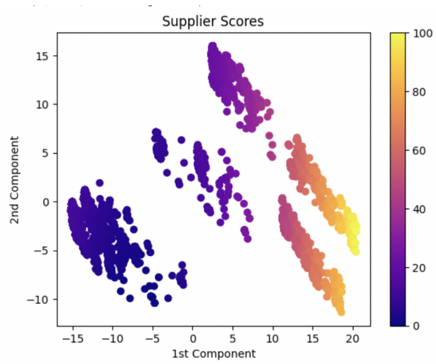

Fig. 6: Supplier scores mapped onto first two components for 5000 training data points

Finally, using these coefficients, we calculate the scores for all 5000 data points. We can see in Figure 6 that the scores improve along the 1st component, with slight improvement along the 2nd component as well.

V. Discussion

A. Analyzing Score Results

ecoScore outputs a score from 0-100 for every supplier in our dataset, allowing us to compare their relative ESG performances. In order to understand our results, we examine Company X and 3 of its 138 suppliers in our training set: Supplier A (X's worst supplier score), Supplier B (X's median supplier score), and Supplier C (X's best supplier score).

We see in Table III that Supplier A (score 2.222/100), satisfies 4/23 criteria, which include environmental and governance factors, but not social factors. Supplier B (score 21.898/100) satisfies 11/23 criteria. These criteria satisfy both environmental and social metrics, including ensuring waste reduction and prohibiting forced labor. Supplier C (score 99.995/100) satisfies 22/23 criteria, making it the company's best supplier. Nearly all of the criteria are fulfilled, meaning that this supplier satisfies substantial parts of all three ESG factors.

While it is promising that Company X is moving far more product weight through the best supplier than the inferior ones, it may consider altering its supply chain by moving production away from Suppliers A and B. Once it has identified these suppliers as weak points, Company X can use our platform to identify alternative suppliers in the same location or product area to use instead.

B. Validation

To verify our proposed scores and test the validity of our model, we apply our methodology to an additional set of test suppliers. We use the FAMD results from the training set of 5000 suppliers to transform 1000 new data points to a lower dimensional space. We apply the same regression coefficients found for the training set to the first two transformed components of the held out test set, and scale them accordingly to compute final scores (Figure 7).

TABLE III: Score Breakdowns for Company X

#	Column	A	B	C
	SCORE	**2.222**	**21.898**	**99.995**
0	totalWeight	306,188	337,951	7,941,451
1	country	India	China	Pakistan
2	product	shirts	shorts	other
3	la_gender_equality	False	True	True
4	en_conserve_water	True	False	True
5	en_zdhc	True	False	True
6	en_carbon_emission	False	False	True
7	la_health_safety	False	True	True
8	la_freedom_association	False	True	True
9	la_living_wage	False	False	True
10	la_training_procedure	False	True	True
11	la_no_child_labour	False	True	True
12	la_no_forced_labour	False	True	True
13	la_wellbeing_programs	False	True	True
14	la_wider_community	False	True	True
15	ma_protect_rights_raw_materials	True	True	True
16	la_social_procedures	False	True	True
17	en_reduce_waste	False	True	True
18	en_reduce_landfill	False	False	True
19	en_no_harmful_chemical	True	False	True
20	en_no_harmful_techniques	False	False	True
21	en_recycled_product_20	False	False	True
22	en_product_can_be_recycled	False	False	True
23	ma_sustainably_sourced	False	False	True
24	ma_respect_animal_rights	False	False	False
25	tr_product_traceable	False	False	True

We can confirm the validity of test data scores by following a similar analysis to that of the original training scores. For example, consider an additional supplier from the test set, Supplier D, with score 21.916/100. Supplier D satisfies 11/23 criteria, which are the exact 11 criteria satisfied by Supplier B in Table III. We see that their scores align very closely. This analysis follows for the full validation set, and we see that for the introduction of new data points we can replicate our methodology with reliable results. Thus, our model can easily accommodate new factories joining our existing supplier data.

C. Limitations and Future Direction

While our scores offer a strong preliminary explanation for the environment, social, and governance factors of each sup-

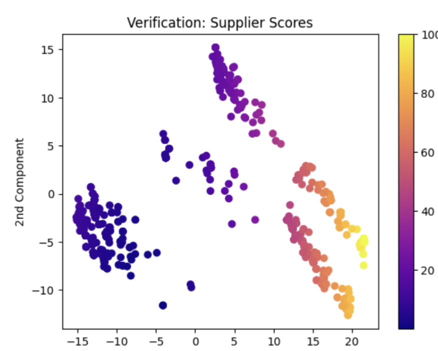

Fig. 7: Supplier scores mapped onto first two components for 1000 test data points

plier in a company's network, their applicability is currently limited by verification and data availability challenges.

Verification of ESG scores is complicated because our project is largely unsupervised and no reliable ESG scores exist to measure our score against. To address this issue, we would like to further explore expert verification; an expert in the fashion supplier industry with knowledge of individual factories could compare factories pairwise to determine if their relative scores are accurate and representative of overall industry opinion. We have not yet been able to carry out such verification at scale, but moving forward, it could strengthen the validity of our scores.

Access to additional data could also enhance the accuracy of our ESG scores. The recency of certifications is essential in determining whether suppliers continue to act sustainably. Suppliers may change their practices and need to be reevaluated to ensure they are still in compliance with the standards set by these certifications. With the addition of the last available date that a certification was obtained, as well as any reported non-compliance, we could improve the reliability of ESG scores in a dynamic dataset.

With these limitations in mind, our current scores should be used in conjunction with other evaluation methods to gain a complete understanding of the supplier's ESG standing within the fashion industry.

VI. Conclusion

The scoring system we have developed uses publicly available data to assign numerical ESG scores to fashion suppliers; its value surpasses that of current solutions, which are largely unreliable or exist only at the broader company level.

Through dimensionality reduction, clustering, and optimization techniques, we are able to simplify the complex problem of calculating quantitative ESG scores for suppliers. This will allow fashion companies to conduct increasingly thorough analyses of their supply chains and take action to improve them. Furthermore, investors and consumers can use the scores as a decision-making tool.

While ecoScore is a promising new solution to a major problem in the fashion industry, it is important to acknowledge that these scores are not yet fully verified due to the scope of the problem and data availability. Future work will focus on acquiring more data and developing additional verification methods in order to maximize the reliability of the relative scoring system.

Acknowledgments

We would like to thank our advisors – Dr. Hamed Hassani, Siddharth Deliwala, and Dr. Jan Van der Spiegel – for their guidance throughout this project. We would also like to thank Heather Williams and Fred Russias at Sourcing Playground for partnering with us and sharing their data. Finally, we would like to thank Dr. Gad Allon and Dr. Sangeeta Vohra from the Jerome Fisher Management & Technology Program and the entire Electrical & Systems Engineering Department at the University of Pennsylvania for their support.

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Business Analysis Addendum

ecoScore

Automated ESG Scores for the Fashion Industry

Executive Summary

EcoScore aims to provide environmental, social, and governance (ESG) scores for factories in apparel supply chains in order to promote more sustainable practices in the fashion industry.

The fashion industry accounts for 10% of global carbon emissions and 20% of global plastic production; labor violations are rampant, with forced and child labor employed in many factories.[1] Such ESG risks in the fashion supply chain are of increasing concern to many stakeholders. Fashion companies increasingly review and analyze their supply chains in order to meet the standards to which they have committed. Investors leverage ESG data to determine potential sustainability risks in targets' operations. Consumers consider sustainability an important factor in purchasing decisions. As a result, demand for accurate and comprehensive ESG scoring in the fashion industry is rapidly rising. However, current ESG metrics are created manually at the company level and are frequently subject to bias and misrepresentation.

Our scores are derived from unsupervised machine learning and regression models trained on publicly available shipping and ESG certification data compiled by Sourcing Playground, a startup working to increase sustainability focus in fashion supply chains. ecoScore's final model outputs a relative ESG score in the range of 0 to 100 for each factory in our dataset, which fashion retailers can leverage to ensure they are meeting ESG benchmarks and investors can use to proactively identify sustainability risks.

Stakeholders

1. *Fashion Companies*: Executives need to monitor their supply chains in terms of ESG metrics and take action accordingly amidst a stricter regulatory environment and rising consumer pressure.

[1] https://www.bloomberg.com/graphics/2022-fashion-industry-environmental-impact/?leadSource=uverify%20wall

2. *Investors*: ESG-conscious investing has been shown to be correlated with higher equity returns and reduced downside risk.[2]
3. *Consumers:* According to a report published in January 2022 by First Insight and the Wharton School's Baker Retailing Center, two thirds of consumers said they would pay higher prices for sustainable goods.[3]
4. *Factories:* While suppliers are not directly involved in our ESG score creation, they are the subject of our ratings. If ecoScore becomes standard in the industry, factories could try to influence the scoring and misrepresent statistics and certifications, so it is important that they remain a third party.

Value Proposition

Fashion companies' sourcing teams need transparency into their supply chains in order to meet regulatory requirements, ease their ESG reporting process, and maintain respect from the public and investors. ecoScore's platform would help these companies understand whether they are meeting their internal ESG goals, as well as pinpoint where to alter their supply chains if their goals are not currently met. By providing a single score using the same model for all suppliers, ecoScore allows companies to easily compare a wide range of factories while also filtering by factors such as location, or types of products produced. Additionally, ecoScore is trained on publicly available U.S. import data and verified supplier certifications, so it is generally more reliable than companies' internal research.

Investors want to understand the supply chains of current holdings and potential targets because ESG risks and resulting public scandals can lead to great financial loss. With ecoScore, investors are able to search for a company and understand its average supplier score, which can act as a proxy for overall ESG practices; for further research, they can examine more detailed individual supplier scores for that company, which may point to areas of risk or potential improvement.

Consumers could use scores as a purchasing decision tool if we make part of our solution (for example, a company's average supplier score) available to the public. They would also be able to hold companies accountable for their sustainability practices, which would encourage brands to make changes in their supply chains to improve their average supplier-based score.

Customer Segment / Market Research

Fashion Brands: Our target customers are apparel retailers operating in the United States. As of 2022, there are 117,025 such companies (a figure we expect to stay relatively constant as growth in the industry is largely based on luxury performance, not new entrants). Because of data availability, we will be able to service large apparel retailers ($1M+ in annual revenue); this

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2
https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/Strategy%20and%20Corporate%20Finance/Our%20Insights/Five%20ways%20that%20ESG%20creates%20value/Five-ways-that-ESG-creates-value.ashx

3
https://www.forbes.com/sites/gregpetro/2022/03/11/consumers-demand-sustainable-products-and-shopping-formats/?sh=7f6b76526a06

gives us 47,325 companies to target.[4] Some of these companies use competitors or have supply chain intelligence in-house, so we assume we will be able to obtain 20% of them, or 9,465 retailers. Assuming an average contract size of $1,000 a month ($12,000 annually), this gives us an annual Total Addressable Market of $12,000 * 117,025 = $1.4B, Serviceable Available Market of $12,000 * 47,325 = $567.9M, and a Serviceable Obtainable Market of $12,000 * 9,465 = $113.6M. Additionally, there is opportunity to move into other industries with publicly available supply chain data.

Investors: According to the Global Sustainable Investment Alliance, 2020 sustainable investments hit $35.3 trillion globally, up 15% from 2018. 25% of this investment came from retail investors, and the remaining 75% is attributable to institutional investors.[5] Because our revenue model will be enterprise subscription-based, we will target institutional investors.

Competition

Major ESG ratings agencies include KLD, Sustainalytics, Moody's ESG, S&P Global, Refinitiv and MSCI. However, an MIT Sloan study found that these ratings are highly divergent (correlation between their ratings for the same companies ranges from 0.38 to 0.71) because they use different sets of privately reported data.[6] Since they rate companies directly, they also underestimate supplier violations and cannot provide insight into how the company can improve at the production level. There exist factory-level ratings agencies, but they are known to be biased as factories pay for social audits themselves and self-report data. ecoScore, in contrast, gives reliable, actionable insights at the supplier level.

We do have direct competition in Higg, a software company that helps companies understand their sustainability and ethical performance with a measure called the Higg Index. However, Higg is aimed towards all consumer goods, while ecoScore's model is specifically trained on data from the apparel industry, making it a more targeted solution for fashion companies.

Revenue Model

Revenue will be monthly subscription-based, with contracts starting at $500/month and increasing with number of users and premium features. We anticipate an average contract size of $1000/month. These figures are based on Sourcing Playground's current pricing, but are raised according to the value we believe the ecoScore scoring system adds to their present offering.

Cost Model

We do not foresee significant costs beyond hosting the platform and providing support to clients. If we were to expand by applying our methodology to other industries, there would be fees to

[4] https://pipecandy.com/list-of-retail-clothing-stores-usa
[5] http://www.gsi-alliance.org/wp-content/uploads/2021/08/GSIR-20201.pdf
[6] https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3438533

acquire additional shipping data; we would consider these costs against market size when selecting our next market.

IP Considerations

ecoScore is a deliverable to the start-up Sourcing Playground in exchange for the use of their data. We have taken care not to reveal data underlying ecoScore throughout Senior Design according to the NDA we signed in the fall, and we will hand over our output to Sourcing Playground this summer.

Appendix

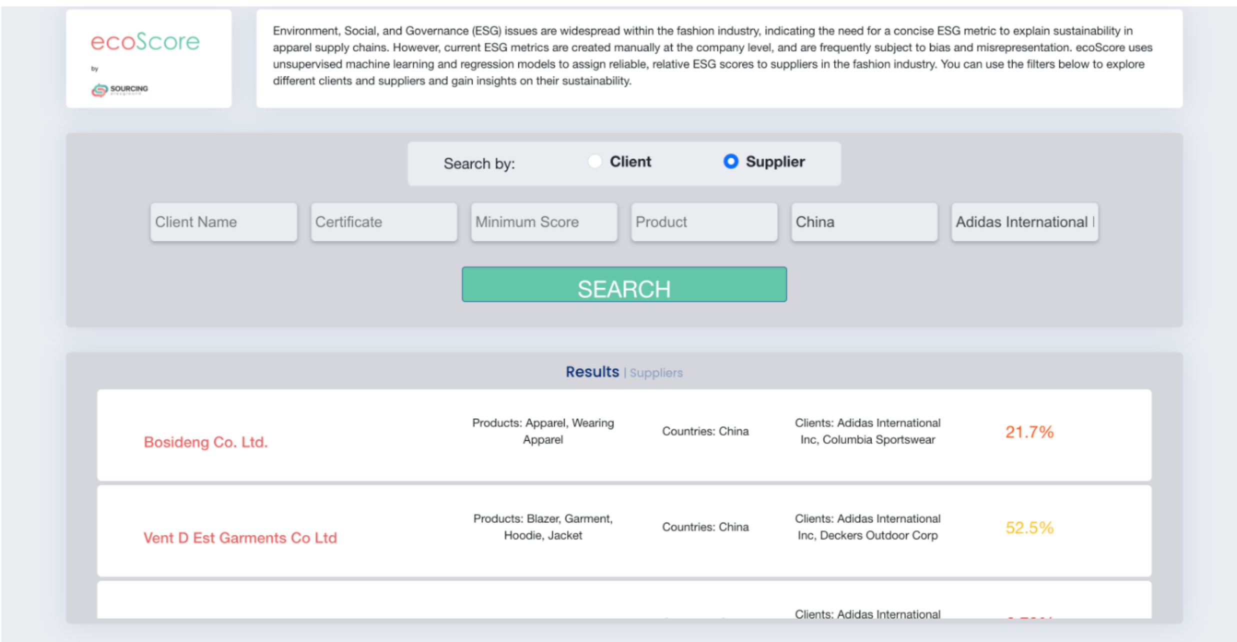

Figure 1. ecoScore UI