face of fonts | 字之魂

Singapore University of Technology and Design
Red Dot Design

Edited By

Chan Luo Qi
Hong Pengfei
Hum Qing Ze

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Abstract

Artificial intelligence (AI) has been around for decades and exploded recently due to the advancements in machine learning algorithms, available big data, and the exponential growth of computing power with decreased cost. Till now near-human performances have been demonstrated in multiple domains, such as computer vision, speech recognition, and Natural Language Processing (NLP).

AI systems are used to analyse and understand information collected by finding patterns from data. Our team explores AI comprehension through the field of NLP which is becoming increasingly empirical and quantitative in their approaches by applying different algorithms and probabilistic models to be able to predict the semantics of a given text. Support Vector Machines (SVM) in particular have been shown to be highly effective at traditional text categorisations. However, current NLP researches are focusing on understanding texts by analysing relationships between words. No work has been conducted on studying the relationship between the semantics of the text and typographical choice.

The advent of the internet has led to the digitisation of typography, previously a hand-crafted art. The mass digitisation of documents leads to a greater standardisation of typefaces and the usage of typography as an aesthetic and mode of communication. Currently, most typographical recommendation systems available to people who need guidance in choosing a typeface are not data-driven decisions but textbooks. In this work, we will implement machine learning algorithms to study different innate characteristics of typefaces, and explore the correlation between typeface design and the meaning it is meant to convey. As there are no prior references, we have gathered our own dataset through publicly available information, applying classification techniques to map the font to a word vector before generating a typeface suited for new corpus of texts. The preliminary data-gathering has revealed a pattern between the mission statement of companies and the typeface chosen in their style guide. To further improve the reliability of our recommendation system, we will utilise a font vector map to allow for greater variation of typefaces recommended beyond our dataset.

This work, which has been overlooked by traditional NLP techniques, may greatly enhance the discovery of semantic meaning in text and create a novel font recommendation system. It has potential to develop a multimodal NLP system that takes into account a greater variety of features beyond analysing only the words within text, drawing inspiration from other multimodal neural networks used for audio-visual recognition that has shown substantial increases in accuracy.

Contents

1 Introduction

In the spirit of the Singapore University of Technology and Design's (SUTD) guiding philosophy, to make a better world through design, we will build an **intelligent system that can support humans in their activities**, applying Machine-Learning (ML) in Intelligence Automation (IA). [1]
Our team explores the application of ML in supervised classification. The goal of supervised learning is to "build a concise model of the distribution of class labels in terms of predictor features".[2]
We aim to build a font recommender using ML and to investigate semantic meaning in typography.
We hypothesise that **typography bears semantic meaning**. To apply ML classification, we first need to understand how to create a meaningfully labelled dataset. Therefore, a literature review was conducted on typography to investigate prior work. Next, a dataset was gathered by first establishing a logical link between typographic design and a potential source of semantic meaning proposed in our literature review.

2 Motivation

A typeface is defined as a digital font, a piece of computer software that contains a collection of vector 'drawings' along with spacing and kerning data that could be accessed through the keyboard. A typeface family consists many variant fonts that share a common design. Previously, **typography has been overlooked as a source of meaning by AI researchers** as its initial purpose was meant to improve the legibility of text and being unique rather than conveying meaning. Therefore, it is hard to create a generalised descriptive framework for different typefaces.
Therefore, we have **chosen to tackle the task of recommending appropriate typefaces** due to the large selection available on the internet and the subjective nature of design. It is timely to adopt this approach as the advent of the internet has led to the digitisation of typography and the mass usage of different typefaces [3] The paradox of choice arises as designers must decide from thousands of typefaces but it is **humanly impossible to know the individual meanings created by contemporary typography** with its variations in colour, 3D effects, material texture and even kinetic movement.[4]
With the help of IA, **designers can have a first cut when choosing a font** that adequately expresses the semiotic meaning intended by their client.

2.1 Current Application of Typography

An entire design industry is centred on consulting for corporations to create a consistent, coherent brand for marketing purposes. These corporate identities prescribe an official typeface which we will use as our dataset.

We highlight three corporations from different sectors to demonstrate examples of typographical design.

1. IBM
   The global company uses a 70 page primer on typographic guidelines highlights, select and explain the rationale for choosing specific typefaces for specific situations. [5]

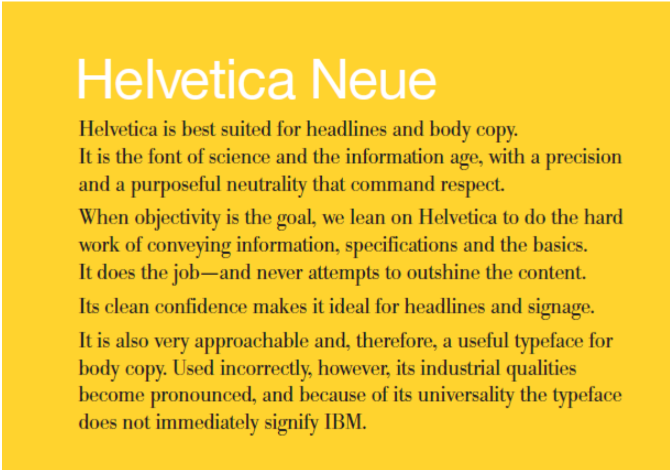


Figure 1: Excerpt from IBM's corporate branding toolkit which explains their choice of *Helvetica Neue* as their primary font. Retrieved form IBM Global Fonts Typographic Guidelines

2. Tesla
   A startup focused on designing and manufacturing electric cars. Tesla's Brand Manual explains that the corporation's primary typeface is *Helvetica* due to it being the "quintessential modern and versatile sans serif typeface" which is "highly legible, economical with space".[6]

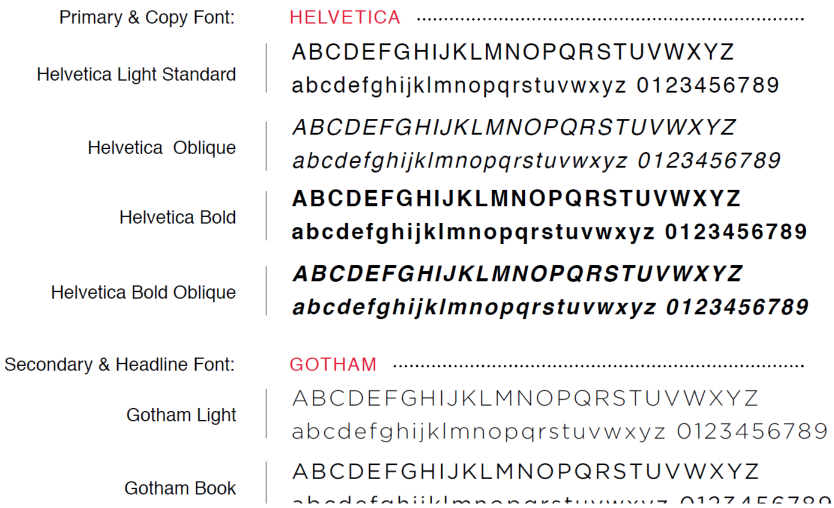
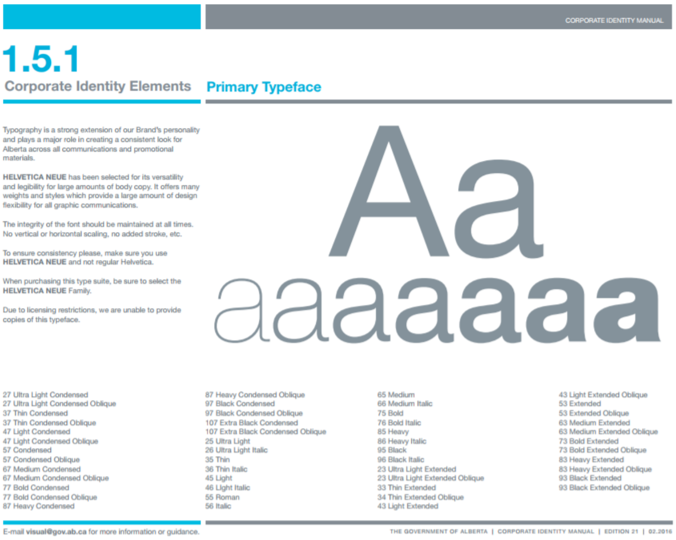


Figure 2: Excerpt from Tesla's corporate branding toolkit which explains its choice of Helvetica as its primary typeface. Retrieved from Teslas's Brand Manual 2010

3. The Alberta Government
   They have chosen *Helvetica Neue* as their typeface due to its "versatility and legibility for large amounts of body copy". [7]


CORPORATE IDENTITY MANUAL

1.5.1
Corporate Identity Elements
Primary Typeface

Typography is a strong extension of our Brand's personality and plays a major role in creating a consistent look for Alberta across all communications and promotional materials.

HELVETICA NEUE has been selected for its versatility and legibility for large amounts of body copy. It offers many weights and styles which provide a large amount of design flexibility for all graphic communications.

The integrity of the font should be maintained at all times. No vertical or horizontal scaling, no added stroke, etc.

To ensure consistency please, make sure you use **HELVETICA NEUE** and not regular Helvetica.

When purchasing this type suite, be sure to select the **HELVETICA NEUE** Family.

Due to licensing restrictions, we are unable to provide copies of this typeface.

Aa
aaaaaaa

27 Ultra Light Condensed
27 Ultra Light Condensed Oblique
37 Thin Condensed
37 Thin Condensed Oblique
47 Light Condensed
47 Light Condensed Oblique
57 Condensed
57 Condensed Oblique
67 Medium Condensed
67 Medium Condensed Oblique
77 Bold Condensed
77 Bold Condensed Oblique
87 Heavy Condensed
87 Heavy Condensed Oblique
97 Black Condensed
97 Black Condensed Oblique
107 Extra Black Condensed
107 Extra Black Condensed Oblique
25 Ultra Light
26 Ultra Light Italic
35 Thin
36 Thin Italic
45 Light
46 Light Italic
55 Roman
56 Italic
65 Medium
66 Medium Italic
75 Bold
76 Bold Italic
85 Heavy
86 Heavy Italic
95 Black
96 Black Italic
23 Ultra Light Extended
23 Ultra Light Extended Oblique
33 Thin Extended
34 Thin Extended Oblique
43 Light Extended
43 Light Extended Oblique
53 Extended
53 Extended Oblique
63 Medium Extended
63 Medium Extended Oblique
73 Bold Extended
73 Bold Extended Oblique
83 Heavy Extended
83 Heavy Extended Oblique
93 Black Extended
93 Black Extended Oblique

E-mail **visual@gov.ab.ca** for more information or guidance.
THE GOVERNMENT OF ALBERTA | CORPORATE IDENTITY MANUAL | EDITION 21 | 02.2016

Figure 3: Excerpt from The Alberta's Government's corporate branding toolkit which explains its choice of Helvetica Neue as its primary typeface. Retrieved from The Alberta Government's Corporate Identity Manual February 2016: Edition 21

2.2 Literature Review

2.2.1 Typographic Meaning

We will proceed to explain the academic literature regarding typography and their significance to our ML classification problem.
Firstly, the idea of the printed word containing two levels of meaning, that of the word image and the idea of the word itself, suggests that we can mine text for a correlation between typography and semantics. These meanings are formed by the associations that exist within the domain into which the typefaces are imported from, with the domain from which they are being used in[8]. This means that **meaning is constrained by the different domains that the typeface is used on**.
It is also proposed that no direct one-to-one relationship exists between typographic form and meaning as it depends on the context in which the given typographical features occur[9]. Therefore, it would be important to **choose typefaces applied in a single context**; we have chosen our area of research to be corporate identities.

The existence of typographical meaning is supported by a paper exploring a syntax of typography through a **system of distinctive typographical features**, potentially a preliminary manifestation of predictor features that ML classification could create[10]. This is further explored by Machin (2007) who offered an inventory of meaning potential suggested through particular typographical designs as "letterforms themselves have become more important as part of the overall meaning of composition"[11].

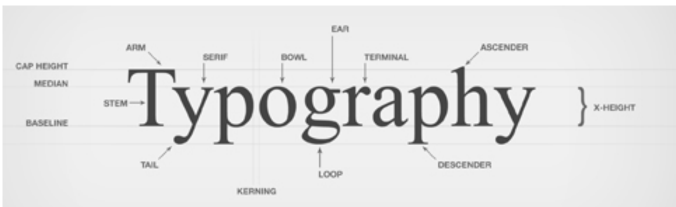


Figure 4: Visual Analysis of Typography, retrieved from "TYPOGRAPHY 101: A BREAKDOWN OF THE BASICS", https://www.pmg.com/blog/typography-101/

Thus, there is potential exploring text typography as a source of meaning by discovering the link between design intent and typographical choice. Current literature is a preliminary investigation of semantic meaning in typography but the approach is humanities-based, taking in subjective interpretations of typography applied on small samples. By using ML, we can **objectively test the hypothesis with larger datasets**.

2.2.2 Dataset intuition with examples

Our preliminary dataset yielded an interesting pattern in the types of companies and the typefaces they choose to represent them.

Figure 5: Companies using *Futura*as a typeface

The font *Futura* was chosen by many lifestyle related brands such as *Red bull, Louis Vuitton, Absolut Vodka, Gucci and Nike.* Typographer Paul Renner based the characters on the "simple forms of circle, triangle and square, but softened them to be more legible and to create a new, modern type that was more than an old revival". The long elegant ascenders and descenders benefit from "generous line spacing and help create this striking and radical typeface that is strong and elegant"[12]. It seemed that *Futura* was chosen for its **modernity**, an image that lifestyle companies need to portray to stay relevant.

Figure 6: Companies using *Garamond*as a typeface

The font *Garamond* is used by many universities and government agencies. Almost all our instances under *Garamond* consisted companies that are in the quinary sector of the economy. *Garamond* is "based on designs by 17th-century French printer Jean Jannon that were themselves based on typefaces cut by Claude Garamond from the 16th century, *Garamond* is an Aldine font that is **elegant and readable**"[12]. These companies tend to be older institutions that have been around for many years. Choosing *Garamond* pays homage to their history and imparts gravitas.

2.2.3 Classification Techniques and Results

A review of different image classification and sentence classification methods was conducted to decide on the best methodology.
The challenge of creating an IA system to recommend typefaces is pertinent to solve now due to the **transferable features in deep neural networks** (NNs) as first-layer features appear not to be specific to a particular dataset or task but general in that they are applicable to many datasets and tasks.[13]
Thus, a two-pronged classification problem is surfaced. Firstly, we will need to **generate accurate predictor features** unique to each font and to classify sentences these fonts are associated with. Next, to analyse the **semantic meaning in the domain these typefaces are utilised**.
NNs require time to train thus we explored a fast classification method, SVMs, to produce preliminary results to act as our baseline model.

2.2.4 Image Classification

The Visual Geometry Group (VGG) networks by the University of Oxford have been made publicly available to facilitate further research on the use of deep visual representations in computer vision.

These networks have achieved state-of-the-art accuracy on the ImageNet Large Scale Visual Recognition Competition (ILSVRC) classification and localisation tasks but **can also be used on other image recognition datasets**[13]. This approach has been utilised on fonts by amateurs exploring the use of ML on helping to classify their own font datasets.

1. Erik Bernhardsson's blog post (2016) on "Analyzing 50k fonts using deep neural networks"
   This resulted in 40-dimension embeddings of all 50,000 fonts

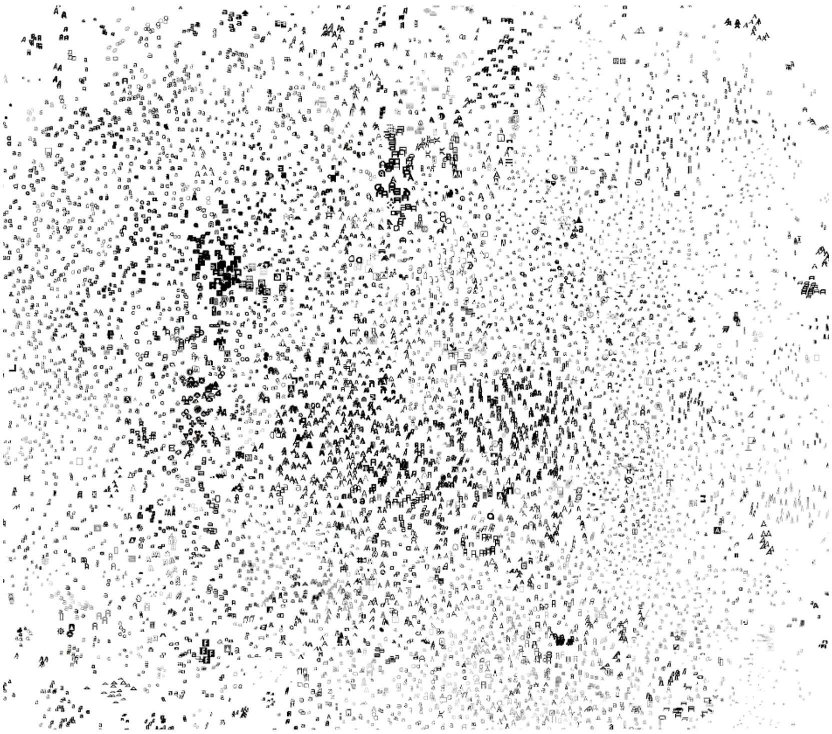


Figure 7: Font Vector Map, retrieved from Analyzing 50k fonts using deep neural networks, https://erikbern.com/2016/01/21/analyzing-50k-fonts-using-deep-neural-networks.html

2. Font Map: An AI Experiment by IDEO (2017)
This experiment is created to allow searching of similar fonts along a map of 750 fonts in a 2-dimensional plane. The algorithm allows for one to classify fonts visually at a scale not possible before.

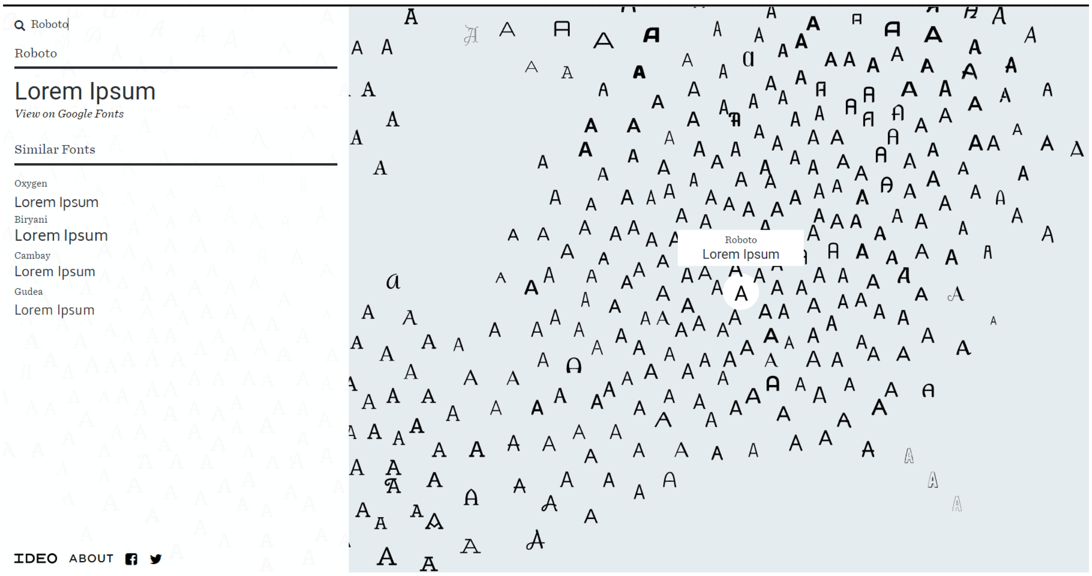


Figure 8: Fontmap by Design Boom, retrieved from http://fontmap.ideo.com/

3. Fontjoy by Jack Qiao (2017).
This experiment generated 200-dimensional embeddings for font pairing purposes which allowed one to search with the cosine similarity function between different font embeddings.

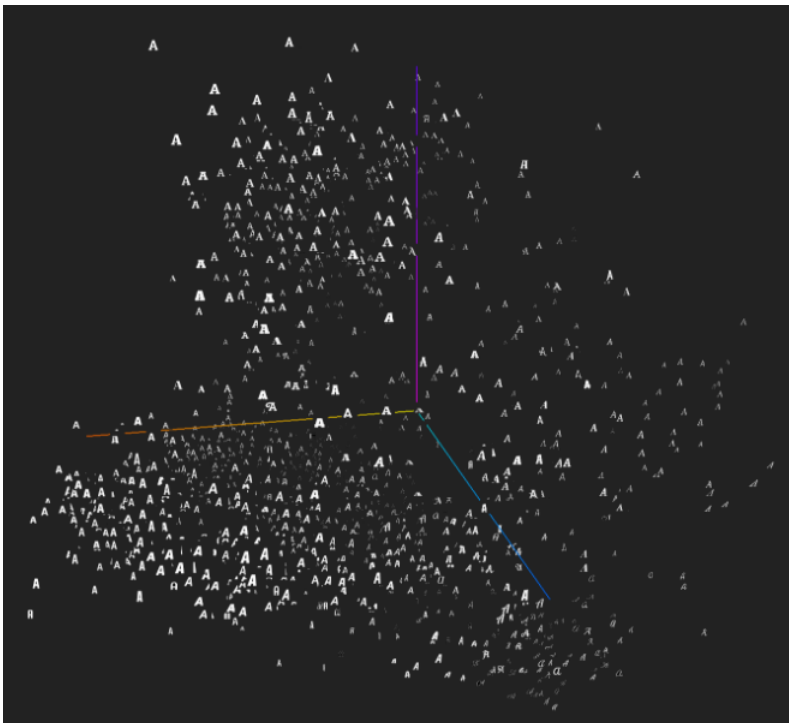


Figure 9: Font vector map, retrieved from http://fontjoy.com/

2.2.5 Sentence Classification: LIBLINEAR

The initial goal of NLP was to extract basic facts such as the relation between two entities[14]. The field is becoming **more empirical and quantitative in their approaches** by applying different algorithms and probabilistic models. Currently, popular techniques are the Naive Bayes, maximum entropy and SVMs.

1. Naive Bayes has been used for relative frequency estimation however it assumes independence between the probability of each word token which does not hold in real life.
2. Maximum entropy has been shown to outperform naive Bayes as their feature function makes no assumptions about the relationships between features relying on feature-weight parameters to act as indicators instead.
3. **SVMs have been shown to be highly effective at traditional text categorisations**. They are large-margin classifiers whose procedure is to find a hyperplane that separates document vectors in one class from those in others with the largest margin possible.

Therefore, we have chosen LIBLINEAR by the Machine Learning Group at National Taiwan University.
LIBLINEAR is an open source library for large-scale linear classification that supports logistic regression and linear support vector machines[15].
We will use the LIBLINEAR text classification model as a baseline as it is highly efficient. LIBLINEAR is the winner of International Conference on Machine Learning (ICML) 2008 large-scale learning challenge (linear SVM track). They have managed to develop LIBLINEAR is to solve an unconstrained minimisation problem using novel and effective techniques to adjust the trust-region size for the classifier. It can perform multi-class classification on our dataset and will assign a unique identification number to each instance within our dataset. Then for each entry, it will add the different instances of the words according to its identification number and generate the different weights of the words. This will form a unique vector that maps the font based on the mission statement data.
We utilised this tool due to its functionality in easily tuning the classification parameters on our development set to provide a preliminary result to guide further investigation.

2.2.6 Sentence Classification: CNN

Recently, Convolutional Neural Networks (CNNs) have achieved state-of-the-art accuracy in sentence classification problems.
This approach is outlined in the paper "CNN for sentence classification" which demonstrated that a simple CNN with little hyperparameter tuning and static vectors achieve excellent results on multiple benchmarks. This was achieved by building a CNN on top of word2vec word embeddings which showed that these **pre-trained vectors can act as 'universal' feature extractors**[16].
This is further explored in "A Sensitivity Analysis of (and practitioner's guide to) CNNs for sentence classification" which gave a general direction as to the need for choosing "model architectures and set accompanying hyperparameters, including the filter region size, regularisation parameters" in order to attain higher accuracy. The paper experimented with different parameters on publicly available datasets that have are commonly utilised by machine learning practitioners. Pre-processing methods are also highlighted such as the need to convert words into tokens and some types of word embedding libraries. Their findings showed:

1. **tuning the CNN to the task at hand**,choosing input word vector representations has an impact on performance but **might not work if there is a lack of sufficiently large training data set**;
2. **filter region size can have a large effect on performance** amd should be tuned;
3. 1-max pooling uniformly outperforms other pooling strategies and
4. regularisation has relatively little effect on performance[17].

Therefore, we will also apply CNNs to investigate if we can achieve a higher accuracy of prediction.

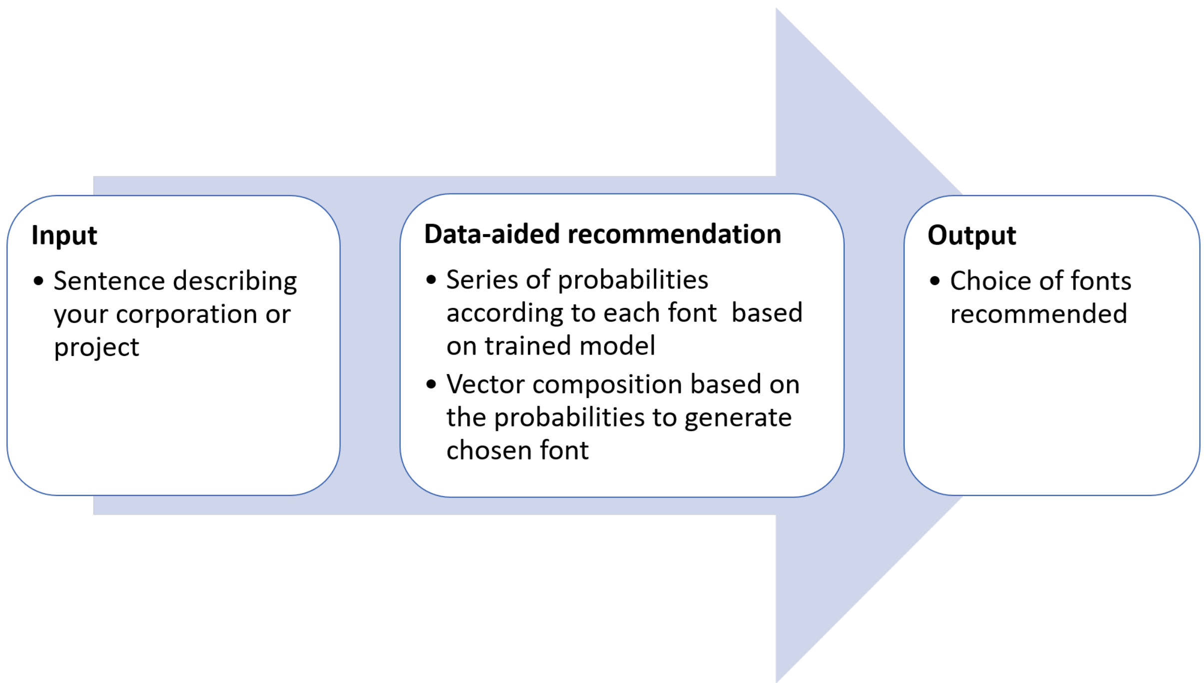
3 Objective

Our best approach to obtain a meaningfully labelled dataset would be to **constrain the context typographical choice is applied and by generating a large enough dataset** chosen from popular fonts for corporate identities.
After pre-processing the dataset, we apply LIBLINEAR as a baseline model before trying CNNs. Finally, we will evaluate our results on real-life applications.

3.1 Product

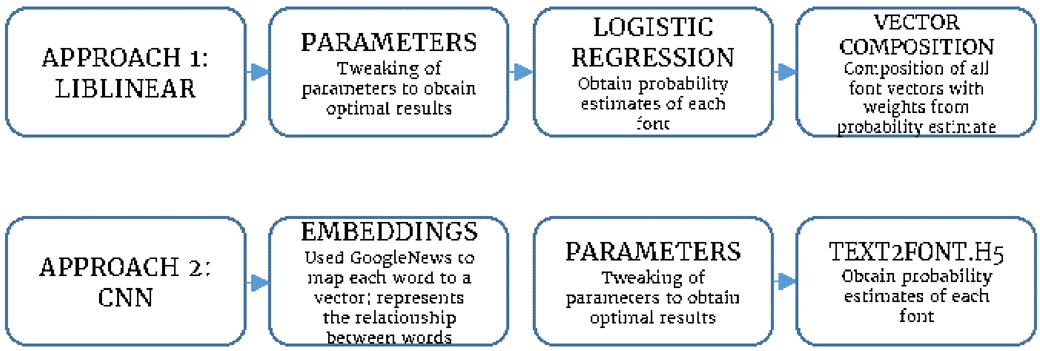
By combining the recent advances in applying image classification to fonts and CNNs for NLP, we will create a font recommender by developing our own model representation of semantic meaning in typography.

3.2 Functional Map of Product



4 Methodology

4.1 Overview



LIBLINEAR method			
1 Data-Processing			
1. Mine typographic choice from corporate branding toolkits	2. Pre-process data using Visual Basic for Applications (VBA) on Excel to tokenise words, remove stop-words and pronouns	3. Split data into training, development and test set	4. Process data using script to allow testing with LIBLINEAR
	Justification		
Official corporate documents provide reliable dataset	Unstructured data format lead to redundancies in data set	To allow for tuning of hyperparameters and testing	LIBLINEAR requires processing to LIBSVM readable format
2 Baseline model			
1. LIBLINEAR produces a model.	2. Predictions on unseen test	3. Tune LIBLINEAR parameters to obtain higher accuracy	4. Further process data to try for only appearances of words

4.2 Data-gathering and Processing

4.2.1 Dataset choice

With some preliminary research and data mining from corporate branding toolkits, 9 different fonts were more popular among corporations. They are:

1. Arial
2. Frutiger
3. Futura
4. Garamond
5. Gill Sans
6. Gotham
7. Helvetica
8. Helvetiva Neue
9. Myriad

These 9 fonts make up our primary dataset, with approximately 50 instances each. For each instance, we extracted the corresponding company's description. These descriptions were all mined from *Linkedin*, a business-oriented social networking site for standardisation purposes.

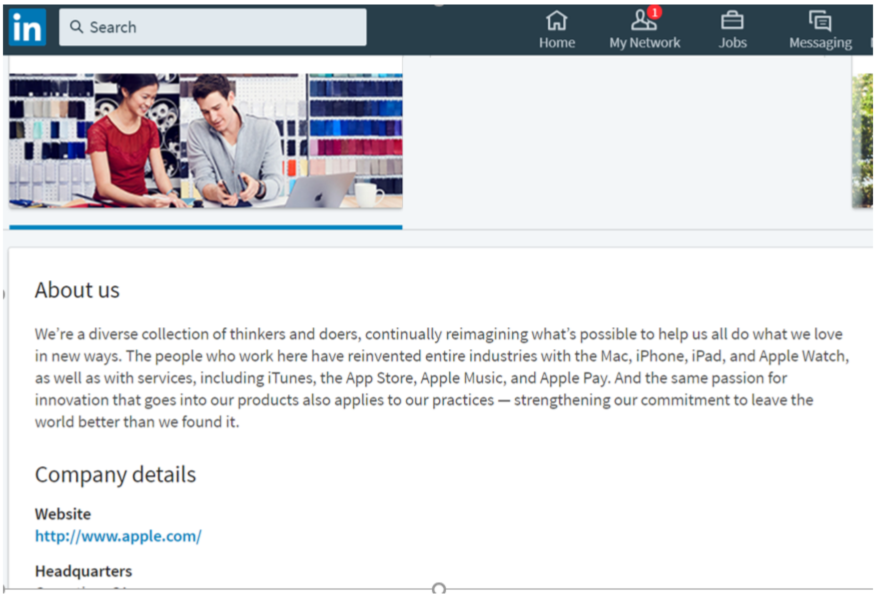


Figure 10: Extracted from Apple's *Linkedin* page, retrieved from https://www.linkedin.com/company/162479/

4.2.2 Data Processing

Natural Language Toolkit (NLTK) is used to pre-process the dataset. NLTK contains a suite of libraries for classification, tokenisation, tagging, parsing and semantic reasoning, which we capitalise on for our research[18].
To obtain a clean dataset, we pre-process the data with 4 different processes:

1. Stop-word removal
   Removal of words with no importance significance. Examples include: this, that, you, it and so forth.

2. Stemming
   Removal of morphological affixes from words, leaving root words. This decreases in the variance of data by collapsing words with the same meaning into one entity.

3. Removal of names
   We use Stanford Named Entity Recogniser (NER). It labels sequences of words in a text in 3 classes: person, organisation and location[19]. By identifying these words, we are able to remove them from our dataset.

4. Sector categorisation
   We classified each company into 5 different sectors according to definition by economists:

   (a) Primary: Agriculture
   (b) Secondary: Manufacturing
   (c) Tertiary: Commercial
   (d) Quaternary: Technological
   (e) Quinary: Public Services

Our dataset is given an added dimension by including economic sector classification as our preliminary data suggested that certain sectors might prefer certain typefaces. This is supported by our literature review where the "domain into which the typeface is imported from" [7] must be considered when discovering semantic meaning.

4.3 LIBLINEAR approach for baseline model

The steps are done in this order:

1. We create a lookup table by mapping each word to an index.

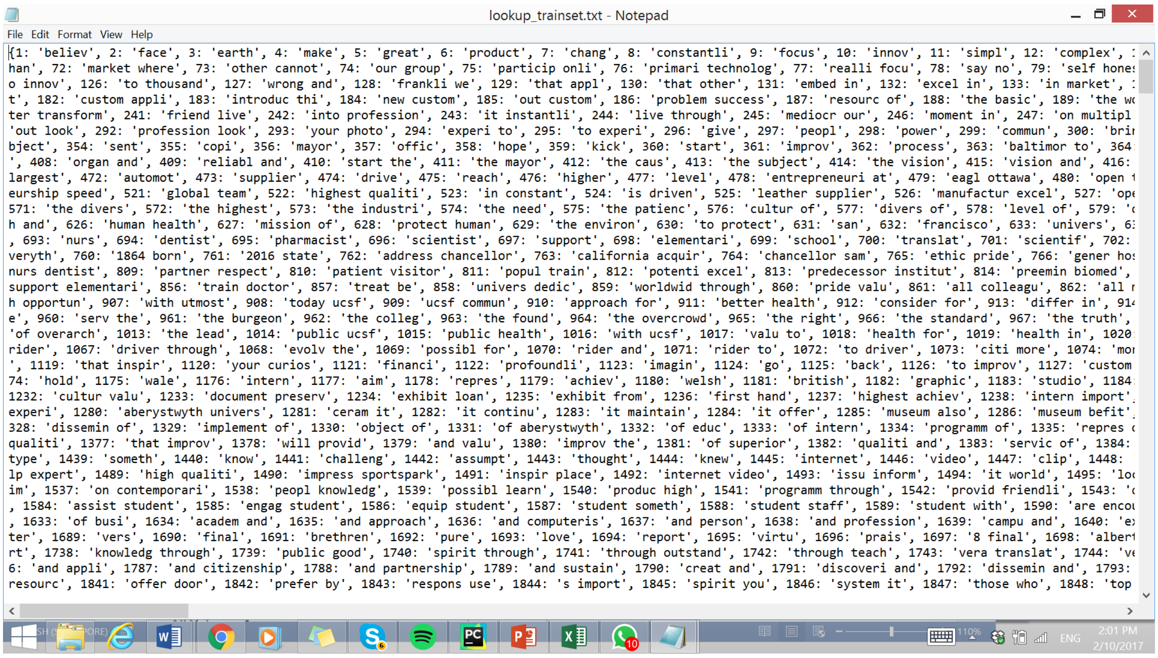


Figure 11: Look-up table created by mapping each word in the training dataset to an index

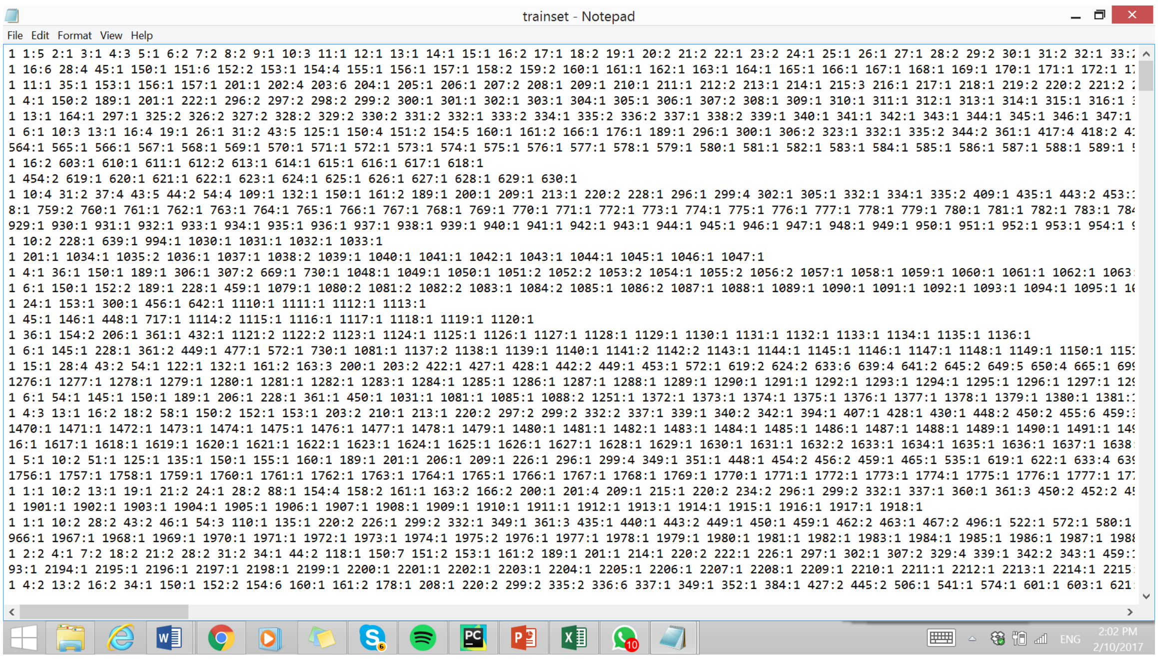
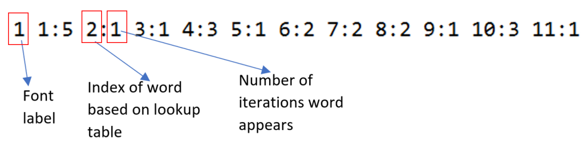


Figure 12: A sample of input file in SVM readable format



3. A model is generated using LIBLINEAR that can be used for testing.

2. We generate our input data in LIBSVM readable format by counting the number of iterations a certain word appears, and appending it to each instance.

4.4 CNN Classification Model

Without lots of training data, we need external semantic information. Therefore, instead of using the conventional bag-of-words (BOW) model, we employ word-embedding models. We have chosen word2vec's GoogleNews corpus which was formed with 3 billion running words resulting in 3 million 300-dimension word vectors. To obtain a larger dataset we split each company description into individual sentences.
To tackle the problem of word relations, we use deeper neural networks. This is illustrated in Yoon Kim's paper titled "Convolutional Neural Networks for Sentence Classification" [15]. It is a simple CNN with one layer of convolution on top of word vectors.
We have included our code here:
https://github.com/Red-Dot-Design/FONT/blob/master/CNN_classifier.py

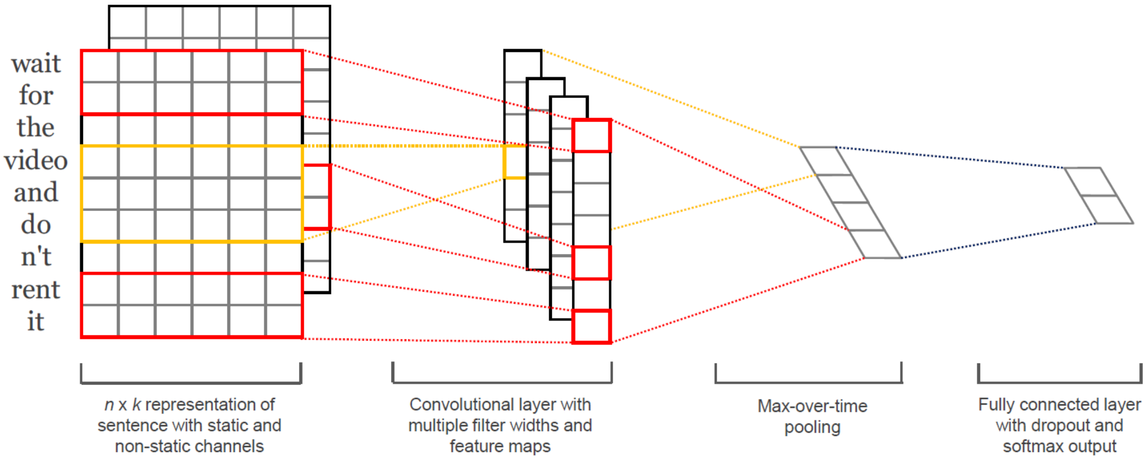


Figure 13: Model architecture for an example sentence

5 Test Results

5.1 LIBLINEAR model test results

To put our hypothesis to the test, we split our data into two portions: 80% training set and 20% development set. The datasets are split randomly each test to obtain an average accuracy rate for highly reliability. We worked with 5 different parameters to determine which combinations would produce the highest probability.
Parameters:

A. All functions

B. Stop-word removal

C. Stemming

D. Removal of location words

E. Sector categorisation

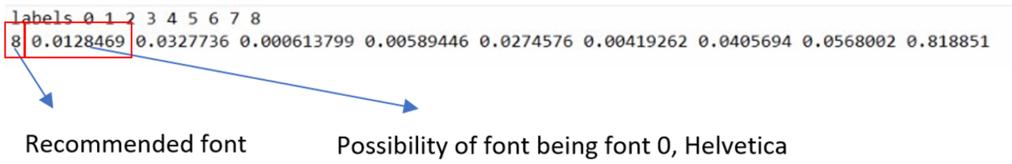
F. No Functions

We concluded from our initial baseline tests that heavier pre-processing allowed for better accuracies with Liblinear.

	Parameters	First test	Second test	Third test	Fourth test	Average
Unigrams	F	13.43%	15.37%	14.82%	14.91%	14.63%
	A	22.22%	21.21%	17.17%	22.22%	20.71%
	B+D	15.15%	22.22%	19.19%	21.21%	19.44%
	B+C	18.18%	17.17%	16.16%	17.17%	17.17%
	C+D	18.18%	24.24%	19.19%	17.17%	19.70%
	B+C+E	19.38%	24.48%	22.44%	20.41%	21.68%
Unigrams + Bigrams	B+C	25.25%	21.21%	20.20%	21.21%	21.98%
	B+C+E	19.05%	21.90%	18.10	16.19%	18.81%

All Values = 1						
	Parameters	First test	Second test	Third test	Fourth test	Average
Unigrams	A	21.21%	23.23%	21.21%	19.19%	21.21%

We also tried setting all values in the training set to be 1 to reflect the existence of words rather than word frequency. However, it did not show much improvement.

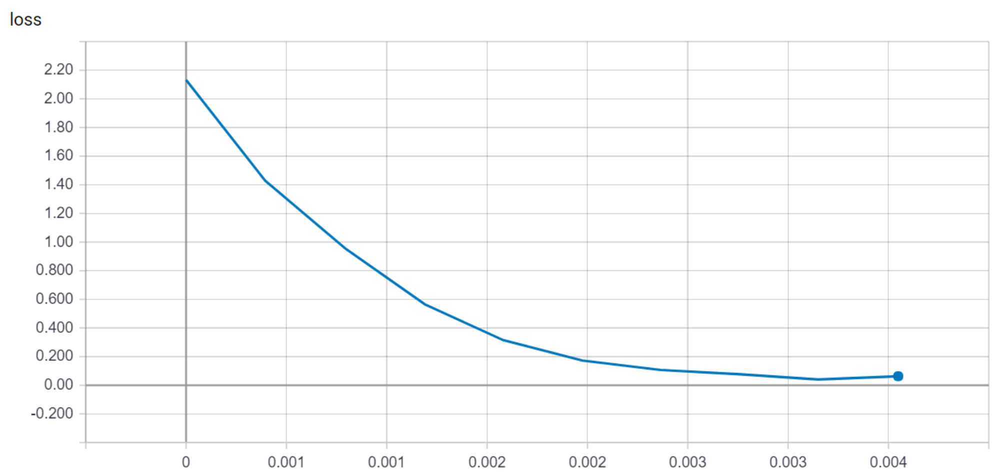


	Parameters	First test	Second test	Third test	Fourth test	Average
Correct label within top 3 probabilities	A	41%	43%	44%	41%	42.25%

We used logistic regression to obtain the percentage of occurrence for each font and to find out whether the correct font label was within the top 3. A higher accuracy was obtained.
In conclusion, baseline results for our preliminary tests average around 20% even when trying different hyperparameters and pre-processing. However, it was still higher than random chance and we decided to proceed with CNNs which should have higher accuracies.

5.2 CNN Accuracy

Parameter grid search performed to obtain best model using experience from tuning LIBLINEAR. Therefore, we found that changing the n-grams and the sentence lengths might have the greatest results. Furthermore, this is supported by our literature review which concluded that input word vectors and filter regions has the most significant increases in accuracy.



Maxlength = 50

nb_filter/ n_gram	1	2	3	4
1000	40.98%	40.53%	39.43%	39.64%
3000	41.87%	40.53 %	41.65%	37.64%
5000	40.01%	42.32%	37.86%	38.53%

Maxlength = 100

nb_filter/ n_gram	1	2	3	4
1000	41.64%	40.98%	38.75%	33.18%
3000	38.75%	38.97 %	39.19%	36.52%
5000	41.42%	41.2%	40.75%	35.85%

Maxlength = 200

nb_filter/ n_gram	1	2	3	4
1000	38.75%	40.53%	39.42%	39.64%
3000	37.86%	39.42 %	37.63%	40.98%
5000	44.58%	45.75%	37.86%	34.96%

The highest accuracy obtained was 45.75% using two n-grams and filter region of 5000. Therefore, we utilised this model to generate font recommendations.

6 Evaluation

6.1 Setting up Test Criteria

As the font recommender is used for real-life applications, the accuracy of the test set is pertinent due to our chosen approach of vector composition where the probabilities act as a guide rather than a prescription of a typeface.
Therefore, we will evaluate our font recommender based on international design awards with a focus on typography, choosing the work of the top branding agencies in the world as our benchmark.
We have chosen two awards:

1. International Society of Typographic Designers (ISTD) Certificate of Excellence
   This certificate is given out to designs that show a "high standard of design in conjunction with a high standard of typography, the criteria being that excellent typography is an intrinsic element of the overall design solution."[18]

2. The Type Director (TDC)
   The TDC is the leading international organization whose purpose is to support excellence in typography, both in print and on screen.
   The TDC holds two yearly type competitions: one for the use of type and the letterform in design and the other, typeface design. We chose the most recent TDC Communication Design Competition which selected 200 winners from over 1800 entries from 50 countries[19].

6.2 Font recommendation process

As our model produces a series of probabilities as a recommendation, we will need to perform vector composition to take into account all input. The vector composition will produce a resultant font vector that can be mapped to an existent Google font. The final recommended fonts will be those that are closest to the resultant font vector. The closest font to the result font vector is measured by:

Euclidean Distance	('composition_vector', 0.0), ('Nunito regular', 6732.1941240298265), ('Rubik regular', 8647.729340776239), ('NTR regular', 11655.124245016548), ('Istok Web regular', 11743
Cosine Distance	('composition_vector', 2.2204460492503131e-16), ('Nunito regular', 0.036959522938429745), ('Rubik regular', 0.087956735450881673), ('NTR regular', 0.092245529241650415),

1. Cosine Distance
   Cosine similarity is a metric for measuring distance between two points using the dot product. It is more often used in analysis texts.
   $$\frac{x \cdot y}{\sqrt{x \cdot x}\sqrt{y \cdot y}}$$

2. Euclidean Distance
   Euclidean distance represents the norm of both vectors. Thereafter, using the font as a baseline, we will recommend their typeface family to give greater variety.
   $$\sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

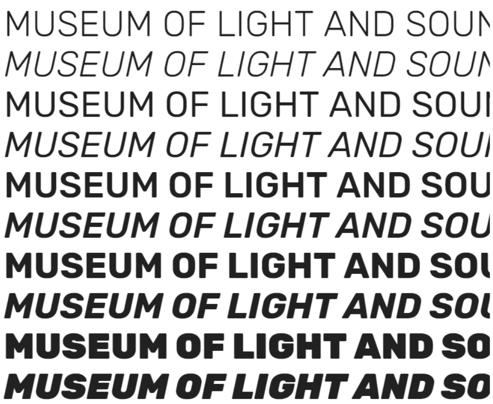
6.3 Comparison

We will now compare the award winning typographical designs with our font recommendations.

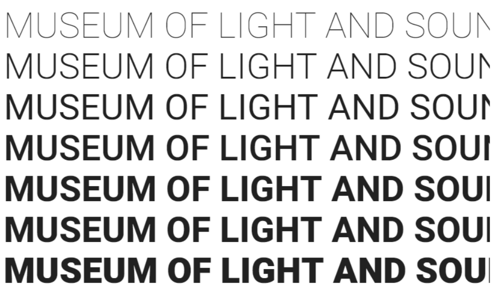
1. **MUSEUM OF IMAGE AND SOUND**
   Studio: ps.2 arquitetura + design
   Art direction: Fabio Prata, Flavia Nalon
   Designers: Fabio Prata, Flavia Nalon, Aurelian Hallhuber, Lisa Moura, Lucas Blat
   "The museum will offer a journey throughout the cultural history of Rio – a well-known and celebrated city for its Carnival, Samba and Bossa Nova. Besides being a cultural center, the museum will also function as a hub to produce and promote culture. Its 9.8 thousand square meters will offer the public an innovative exhibit design in order to digitally display the institution's collection that includes different documents, photographs, billboards, records, footage, videos, newspapers clippings, and texts. MIS will also house and display the Carmem Miranda Museum collection.
   The museum's program includes short and long term exhibitions, research offices, educational activities room, a 280-seat theater/cinema, a shop, a cafeteria, a panoramic restaurant, a bar/rooftop terrace, a nightclub and an observation deck, as well as a kiosk on the beachfront."

Figure 14: Logo of Mis Museu Da Imagem E Do Som, retrieved http://www.mis.rj.gov.br/about-us/

Our Recommendations
1. RUBIK



2. HEEBO



2. **THE PALESTINIAN MUSEUM**
Studio: venture three
Art direction: venture three, Stuart Jane, Grant Dickson, Tim Jackson
Designers: Nadine Chahine (Arabic)
"The Palestinian Museum is an independent institution dedicated to supporting an open and dynamic Palestinian culture nationally and internationally. The Museum presents and engages with new perspectives on Palestinian history, society and culture. It also offers spaces for creative ventures, educational programmes and innovative research. The Museum is a flagship project of Taawon-Welfare Association and one of the most exciting new cultural projects in Palestine."

Figure 15: Logo of The Palestinian Museum

Our Recommendations

1. Oxygen

the palestinian museum
the palestinian museum
the palestinian museum

2. Hind

the palestinian musuem
the palestinian musuem
the palestinian musuem
the palestinian musuem
the palestinian musuem

3. Hind Siliguri

the palestinian museum
the palestinian museum
the palestinian museum
the palestinian museum
the palestinian museum

3. **PLENTYFULL**
   Designer: Mark De Winne, Singapore
   Studio/Agency: Parable Studio Pte Ltd
   "Plentyfull is your definitive place of restoration, tucked away in the thick of city jungle bustle. Run on love, laughter, and an ever-changing food menu steered by the freshest seasonal ingredients sourced straight from the farmers and spearheaded by creative culinaires. The kaleidoscope of diverse cuisines, all made from scratch, is accompanied by buttery whiffs of freshly baked pastries adrift from our kitchens.
   The space that serves great food, evolves from a wholesome market table luncheon spread, to an intimate full service restaurant come nightfall. At Plentyfull, there's something to rejuvenate the senses, any time of day."

Figure 16: Extract from Plentyfull's braning toolkit depicting its chosen primary typeface. Retrieved from http://parable.sg/news/plentyfull

Our Recommendations

1. Shanti

Aa Bb Cc Dd Ee Ff Gg Hh Ii Jj Kl

2. Open Source Sans Pro

Aa Bb Cc Dd Ee Ff Gg Hh Ii Jj Kl

4. **Tom's Town**
   Designer: Kevin Cantrell, Salt Lake City, Utah
   Studio/Agency: Kevin Cantrell Studio
   "Tom's Town Distilling Co. draws its name and inspiration from the country's most polarizing and corrupt political boss, Tom Pendergast. Pendergast had roots in the liquor business as a saloon keeper and as the founder of a wholesale liquor company."

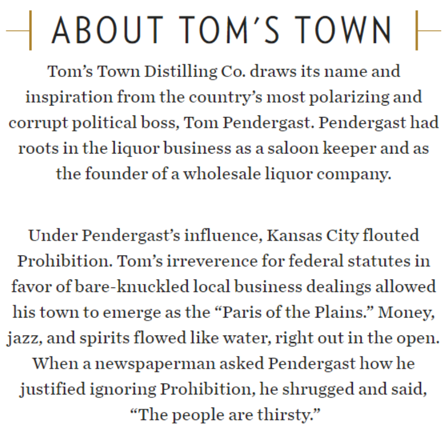


Figure 17: Screen capture of Tom's Town website description depicting their chosen primary typeface. Retrieved: http://www.toms-town.com/#

Our Recommendations
1. Shanti

ABOUT TOM'S TOWN

2. Droid Sans

ABOUT TOM'S TOWN
ABOUT TOM'S TOWN

5. **Bythenorth**
Designer: François Xavier Saint Georges and Daniel Robitaille, Montréal
Studio/Agency: Bythenorth—furniture designer/maker and visual designer
"A good design is starting with an excellent idea. Leading to a bucket of added spontaneity. Free flow gestures in the making. This attracts us a lot. Unexpected, playful results: it becomes beautiful and useful. When it comes to furniture, we believe that good design should be free and sharp. As an eagle above the forest."

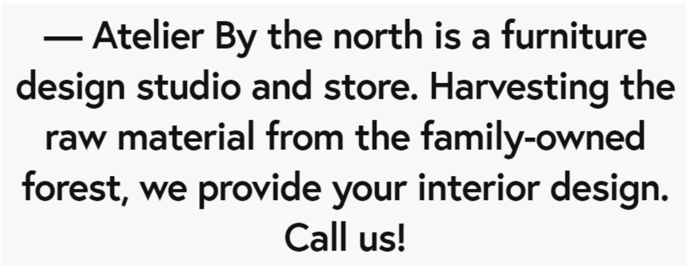


Figure 18: Screen capture of By The North's website description depicting their chosen primary typeface. Retrieved: http://www.bythenorth.com/english/

Our Recommendations
1. Nunito

Atelier By the North is a furnitu
Atelier By the North is a furnitu
Atelier By the North is a furnitu
Atelier By the North is a furnitu
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Atelier By the North is a furn
Atelier By the North is a furn

2. NTR

Atelier By the North is a furniture

6.4 Limitations

As corporations have multiple beachheads when running their operations, there is substantial difficulty in getting a dataset that is relevant. Sometimes not all information is contained within the company's webpage. Therefore, we had to continuously tweak our dataset to be able to generate a representative model of the semantic in typography. The logical link that designers create a corporate identity according to a company's brand will mean that we need to find out a succinct and accurate description of a company. There are also limitations in the dataset due the randomness in choosing the companies; no specific economic sector was targeted. Moreover, the typefaces chosen might not entirely focus on the motivations in the meaning the company might try to convey, but rather limited by the accessibility of fonts and considerations on readability.

6.5 Potential

The font recommender can be better refined. Following the design thinking framework, we will need to conduct interviews with designers to find out the industry landscape and pain points to cater to their needs. We could also conduct market tests with budding designers and students who might need to choose a font for their projects. Using these tests, we can create user personas to improve the usability of the font recommender so both professionals and laymen can utilise it.
As we were working on the project, a design consultancy was formed called Brandmark.io. The consultancy uses ML to generate logos composed of an icon, typography and color scheme. Despite some success, they acknowledge that the problem is challenging due to no "hard rules" and that the "aesthetics of typography is heavily subject to taste". Navigating their site gives a rudimentary logo design matched with font pairing. However, their value proposition is the ability to give a quick mock-up aided by AI.

Figure 19: "Test Company" used with Brandmark.io's AI-powered designer

7 Further work

7.1 Academic research

A review of current NLP techniques concluded that supervised learning approaches have better results. However most of these systems use features based on a shallow analysis on the text thus it was proposed to have a new direction focused on deep analysis[19]. There is potential to explore further using multimodal neural networks to conduct deeper analysis on text beyond word tokens to establish greater context for better semantic analysis.
Several researchers have shown that a multimodal neural network architecture can create better predictions from a greater diversity of features. More accurate results have been obtained by combining lexical and machine learning techniques to classify emotions in text according to Ekman's six emotional categories. [20]. This is further supported by research on combining audio and visual recognition deep learning networks resulting in a higher accuracy of predictions on audio-visual classification of isolated letters and digits[21].
With further tuning of the parameters and gathering a larger dataset, the accuracies achieved will be higher. By combining our typographical semantic analysis with current NLP techniques, we might be able to create a multimodal NLP algorithm that achieves even higher accuracies in the future.

As this is currently unprecedented research, there is much potential to further develop our dataset and classification method. One area of research would be to extract the weights from each neural network layer to explore whether each layer has "learnt" a particular feature of the font. For example, in image classification tasks some neurons have "learnt" the ability to identify edges in an image or certain objects. We would expect something similar with our neural network.

7.2 Font recommender

As our product has real-life applications, we would have to build on our current work with the frame of a business case rather than an academic endeavour. We will require user insights and further testing, potentially building on the product to be able to generate first cuts for all aspects of the corporate identity to liberalise design for the layman.

8 Conclusion

In the present work we have described a baseline experiment with LIBLINEAR before a series of experiments using CNN. The best trained model has provided a surprisingly similar result to that of real life international design award winning typefaces.
Our results act as a preliminary foray into using typography as a source of meaning and we encourage greater research and collaboration to build a larger corpus of research on semantic meaning in typography by building larger datasets and exploring different domain uses.

References

[1] Accenture PLC. Coming of age of artificial intelligence: Disruption transformation ahead, 2015.

[2] P.E. Pintelas S. B. Kotsiantis, I.D. Zaharakis. Machine learning: a review of classification and combining techniques, 2006.

[3] Keith Chi hang Tam. Digital typography: a primer. 2006.

[4] F Serafini and J. Clausen. Typography as a semiotic resource. 2012.

[5] IBM. *IBM Global Fonts Typographic Guidelines*. 2010.

[6] Tesla. *Brand Manual*. 2010.

[7] The Alberta Government. *Corporate IDENTITY Manual*. February 2016.

[8] T Van Leuwen. Typographic meaning. 2005.

[9] N Norgaad. The Semiotics of Typography in Literary Texts, A multimodal approach. 2009.

[10] D Machin. *Introduction to multimodal analysis*. London : Hodder Arnold, 2007.

[11] J. Yosinski, J. Clune, Y. Bengio, and H. Lipson. How transferable are features in deep neural networks? *ArXiv e-prints*, November 2014.

[12] K. Simonyan and A. Zisserman. Very Deep Convolutional Networks for Large-Scale Image Recognition. *ArXiv e-prints*, September 2014.

[13] J Hirschberg and C Manning. Advances in nlp. 2016.

[14] Chang K Hsieh C Wang X Fan, R and C Lin. Liblinear: A library for large linear classification. 2017.

[15] Y Kim. Convolutional Neural Networks for Sentence Classification. 2014.

[16] Y Zhang and B. Wallace. A sensitivity analysis of (and practitioner's guide to) convolutional neural networks for sentence classification. 2016.

[17] Edward Loper Bird, Steven and Ewan Klein. *Natural Language Processing with Python*. AO'Reilly Media Inc, 2009.

[18] Jenny Rose Finkel, Trond Grenager, and Christopher Manning. Incorporating non-local information into information extraction systems by gibbs sampling. 2005.

[19] Y Jain and A Sandhu. A review on emotion detection from text using machine learning techniques. 2015.

[20] Koroveshovski K Gievska, S and T Chavdarova. A hybrid approach for emotion detection in support of affective interaction. 2014.

[21] J Ngiam, M Khosla, A an Kim, J Nam, H Lee, and A. Ng. Multimodal deep learning. 2011.