Project: **Graded Product with PERT**

Team: AOEC

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https://github.com/AOEC-CLOUD/GRADEDPRODUCTS

Dev Post URL

https://devpost.com/software/graded-product-with-pert

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The delay in submitting the explanation for GS1, was due to submission being a conceptual framework that required different specifics to be illustrated

Revised as a working example for machine learning, GDSN Data will need to be retrieved by the Atrify API(s) using JSON and thereon GTIN numbers (13 digit numbers prefixed by 0 for Germany and 8 for India) will need to be mapped to SR numbers (that have a Grade or Nutrition Score associated with them).

The mapping of the GTIN numbers to (Specific Requirements for Honest Products) SR numbers is done to help the Honest Products programme elevate its vision across regions that the GS1 is associated with, and thereon to India and other neighbouring regions.

The expectation of adding a Nutrition Score is already part of the GS1 problem solving for FMCG products in Germany and select regions.

The issue is that the Nutrition score (called Nutri-score) may not be consistent, apt or may not help recommendation or learning of customer requirements for honest products.

As the challenge is about demand based products or individualization, we need to ensure the GTIN numbers of products that may or may not have a consistent or apt Nutri-score need to be graded to ensure one more pass, where a honest and ethical PERT algorithm associates a grade to the FMCG product.

A grade today as a working concept can be a simple number, as people are used to numeric ranking of products or scores.

For example, we have considered the following

Grade 1 is assigned to FMCG products that are an Asset for the GS1 network, where supportive research and findings confirm the product is excellent for being honest and ethical (as highlighted in the landing page).

Grade 1 with P2PC (Plan to Prevent and Control) is assigned to FMCG products that are an Asset but have been found to part of a Plan to Prevent and Control diseases known to need remedial eating habits.

Grade 1 with C-V-O-D-C (Chartered Incidence Response Policy specific Variance and Overhead data collection), where the grade is assigned to the FMCG products that are ASSETS for consumerism but have a chartered incidence response policy that evaluates variance in any consumption issues and also calculates the overhead in the FMCG industry to address this variance,

...Today we are amidst the need to contain the COVID-19 crisis, this may be an overhead for the FMCG industry, where the overhead may be at the manufacturer end, or the retailer end or the supplier end or the customer end, due to the fact that the infection has no conclusive transmission dynamics as yet.

...For any overhead, the customer dimensioning & proportion analytics, the continual demand analytics and the cost influencer analytics help in demand/supply equilibrium.

Scientifically, a food manufacturer.. or FMCG manufacturer will cut down costs to meet the target market's demand, but this cost cutting should not be an overhead that the GS1 network cannot estimate, to help ensure the honest and ethical programme is successful.

Grade 2 is assigned to FMCG products that are green or organic for the GS1 network, where supportive research and findings confirm the product is actually green or organic in agri-culture and CO2 lifecycles (as highlighted in the landing page).

Grade 3 is assigned to FMCG products that are natural or fresh for the GS1 network, where supportive research and findings confirm the product is actually natural or fresh in graded ingredient-culture and apriori principles (as highlighted in the landing page).

Grade 4 is assigned to FMCG products that are frozen or preserved for the GS1 network, where supportive research and findings confirm the product is actually with HGI delimiters-culture and apriori principles (as highlighted in the landing page). We know that frozen or preserved food can contain unknown or known bacteria or viruses.

Grade 5 is assigned to FMCG products that are other categories for the GS1 network, where supportive research and findings confirm the product is honest and ethical if relevant or of adequate understanding (as highlighted in the landing page).

<u>As ground-level expectation</u>

We know that codification, labelling and nutrition scores are the steps towards healthy products, but we also find that the score is only for well-defined consumables, but there could be products that are with a Nth connection facade, where their recognition or understanding may be early at this stage.

Disasters, epidemics, endemics, pandemics or deterioration of economics may make it important to produce certain FMCG products that are associated with a Nth connection facade and not just what we call as target markets or target market profiles (as highlighted in the landing page).

The Nth Connection Facade projects that a FMCG product has 'N' different connections where these connections could be categorized into the following:

1. Fit for Environmental, Social and National health goals

2. Fit for Economic demands

3. Fit for Social interests

4. Fit for Political demands

5. Rooted interests (business policy)

6. Unified ownership for a HGI makeup## What it does (Solution and Approach)

The Customer HP (Honest Product) Requirement Learning Tool reviews customer requirements “for honest products” to find that product barcodes or score requests coming to the GDSN Hub or Information Centre

1. Can have repetitive text in the description or problem details

2. Can have some standard steps that the customer can take to find resolution for some questions or problems

3. Can have responses / resolutions that do not need human intervention (an interest for the GS1 Hackathon and its roadmap)

Inference

1. The GDSN Hub/Information Centre experts infer that buckets of honest product requirements can be created through a machine learning algorithm based on the past customer honest product requirements.

2. For each bucket, a set of corresponding standard resolutions can be associated to learn about interests and/or reduce time spent per request or call.

3. Whenever a new customer (honest product) requirement comes to the GDSN Hub or Information Centre, a machine learning algorithm would identify the bucket to which the new honest product requirement should be tagged to, where this should help come up with a standard resolution and then help report the same across to the customer.

Methodology

In the solution,

1. The customer honest product requirements in the repository are clustered using a combination of (a) **Text-analytics** of “text fields” with select descriptions, (b) **the time estimated or taken to resolve each requirement and** (c) **a categorization variable** that categorizes the nature of honest product requirement.

2. The Text-analytics technique is based on **Word2Vector**

3. The clustering technique is based on **DBSCAN**

4. The **Cosine similarity algorithm** is used to classify honest product requirements to fit within one of the buckets created (where this is based on text categorization)

How we built it

We at AOEC are developing the idea using the Python & Anaconda framework and different libraries for data analysis, array processing, Natural language processing, Text-analytics & clustering, visualizing of clusters, request or remedy description similarity

The details of the libraries follow:

Specific libraries to load data, perform computation and display output are

(a) Pandas – Data acquisition library

(b) numpy – Array processing library

(c) nltk.data and nltk.corpus – Natural language processing library

(d) gensim and gensim.models – for text analytics and clustering, where the Word2Vector function is used

(e) gensim.models.keyedvectors – to import keyed vectors

(f) matplotlib – for visualizing clusters

(g) sklearn.cluster – to import DBSCAN for clustering

(h) sklearn.metrics.pairwise – to import cosine-similarity to find out request description similarity

Code snippets in the proof of concept (step wise)

(1) To import libraries and functions

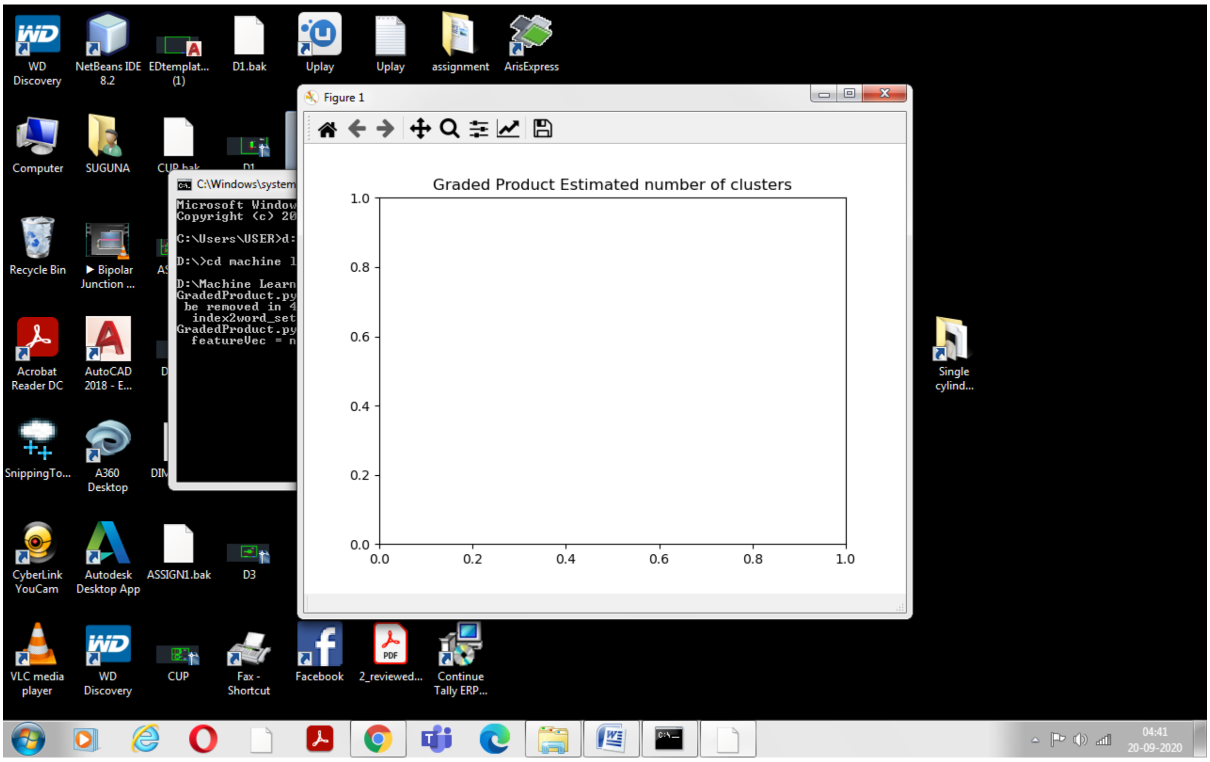
(2) To load data

(3) For filtering of honest product requirements based on groups for "honest products categorization" (where there are 5 0r 6 Grades and one GDSN_Transaction Hub category, it is noted that the Transaction Hub category can be exploded further when the proof of concept is developed into a complete application for GS1)

(4) Text analytics to create the training data for the machine learning algorithm

(5) Running of the clustering function

(6) Assigning of a new honest product requirement to a correct bucket based on the cosine-similarity function



Work in progress Code Snippet Details (refer AOEC-CLOUD/GradedProduct in the GitHub)

We are yet to work on code snippets for the functions of (b) **Deep Learning** & (c) **Recommendation Systems** to build more (1) awareness, (2) sensitivity, (3) preparedness and (4) theme smartness (for example, **Honest & Ethical FMCG products**) to meet demand/supply relativity with transparency to improve health, wellness and immunity.

Good wishes and warm regards.