The Converging Triangle of Cultural Content, Cognitive Science, and Behavioral Economics

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Abstract. How online cultural content is chosen based on conscious or subconscious criteria is an central question across a broad spectrum of sciences and for the entertainment industry, including content providers and distributors. To this end, a number of tailored analytics forming the backbone of recommendation engines specialized for retrieving cultural content are proposed. Their strength derives directly from well-established principles of cognitive science and behavioral economics, both scientific fields exploring aspects of human decision making. Another novel contribution of this conference paper is that these analytics are implemented in Neo4j expressed as Cypher queries. Various aspects of the cultural content and digital consumers can be naturally represented by appropriately configured vertices, whereas edges represent various connections indicating content delivery preferences. Early experiments conducted over a synthetic dataset mimicking the distributions of preferences and ratings of well-known movie datasets are encouraging as the proposed analytics outperformed the baseline of a multilayer feed-forward neural network of various configurations. The synthetic dataset contains enriched preferences of mobile digital consumers of cultural content regarding literature of the Greek region of Ionian Islands.

Keywords: Cognitive science · Behavioral economics · Cultural content · Content delivery · Graph recommendation · Graph databases · Graph analytics · Neo4j · Cypher · Humanistic data

1 Introduction

Interpreting and predicting, within a reasonable degree of error, the selection of online cultural content or even a sequence of such selections, has been a central topic in various scientific fields ranging from economics and social science to

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artificial intelligence (AI) and machine learning (ML) as well as to interested parties such as platform managers and content providers.

During the current decade the creation cultural content has reached unprecedented levels in terms of number of generators, languages, modalities, and topics. Given the ease of access to equipment ranging from an off the shelf smartphone to a digital camera as well as the prevalent culture encouraging creativity and originality, a considerable number of independent content contributors has been added to established entities such as cultural foundations, academic institutions, government agencies, and private organizations.

The primary research objective of this conference paper is to lay the groundwork for graph analytics based on sound principles of both behavioral economics and cognitive science and tailored for the recommendation of personalized delivery of cultural content. Recommendations not only assist in navigating among the plethora of available digital cultural content, but also help the digital consumer discover new and potentially interesting material. The contribution of this work is that augments the few cultural analytics, especially those implemented over a graph database, whereas giving new directions to them.

The principal motivation besides this work is that the delivery of cultural content requires specific conditions which differentiate it from ordinary digital entertainment. Specifically, cultural, educational, and location parameters must be taken into consideration.

The remaining of this work is structured as follows. Section 2 briefly reviews scientific literature regarding recommendation engines, behavioral economics, and cognitive science. The architecture and the queries of the proposed recommendation system as well as the intuition behind them are given in Sect. 3. The results of the experiments conducted so far with the proposed analytics and the baseline neural networks (NNs) are presented in Sect. 4. Finally, the conclusions and the directions for future work are given in Sect. 5. Tensors are represented with capital calligraphic letters, whereas capital and small boldface are reserved for matrices and vectors respectively. Table 1 summarizes the notation of this work.

Table 1. Notation of this conference paper

Symbol	Meaning
$\triangleq$	Definition or equality by definition
$\{s_1, \ldots, s_n\}$	Set with elements $s_1, \ldots, s_n$
$\|S\|$	Set cardinality
$\tau(S_1, S_2)$	Tanimoto similarity coefficient for sets S_1 and S_2
$c(\mathbf{d_1}, \mathbf{d_2})$	Cosine similarity coefficient for vectors $\mathbf{d_1}$ and $\mathbf{d_2}$
$\mathbf{O}_{n_1,n_2}$	Zero matrix of dimensions $n_1 \times n_2$

2 Previous Work

Scientific literature abounds with works regarding general- and special purpose recommendation systems for various tasks relying on diverse technologies. Then, a shift towards adaptive and content-based recommendation systems was made as is made clear from works like [26] and [21]. Initializing a recommendation system and associate issues are explored in [20]. Recently, with the advent of Semantic Web, incorporating trust into recommender systems has been also added to the line of research [1]. Applications of recommendation systems include software engineering as discussed in [28].

Cultural analytics are the offshoot of social sciences and data science aiming at providing deeper insight into the individual and collective cultural background [23] and [24]. Possible transitions to data-driven cultural analytics are discussed among others in [14], whereas applications include tracing social patterns in social media [29] such as Instagram [15] and flickr [32].

Behavioral economics is a field studying human behavior from a decision-making point of view [5]. Recurring major topics include conflict and compliance [30], corporate management [19], public policy [7], rewards and gamification [2], and learning to evaluate rational choices with a multitude of criteria [9]. The psychological grounds of the field are given in [16], while a recent overview of the field is given in [36].

Cognitive science covers the study of human mental activity at various levels [31]. Sources include high level psychological and sociological observations, education, as well as low level data about brain physiology and connectivity [8]. A framework for evaluating decision making is presented in [13] and mental decision models in [37]. A thorough revision of human decision making from a cognitive science perspective is given in [4]. The relationships between brain functionality and the structure of the human nervous system are explored in [33], while the connections between cognitive sciences and language are investigated in [3].

Tensor algebra is the generalization of matrix algebra to three or more dimensions [17]. Traditionally, tensors were widely applied to singal processing applications such as brain MRIs [35], MIMO radars [25], multispectral imaging [27], and face recognition [34]. However, recently tensor analytics have been implemented over Neo4j in order to combine structural and functional higher order analytics in [11]. Moreover, a genetic algorithm for approximately clustering a tensor with spatiosocial data has been implemented in [12].

3 Analytics

3.1 Implementation

Figure 1 depicts the overview of analytics architecture. In essence, the architecture is a long feedback loop where digital consumers are given suggestions as to which piece of cultural content to select based on their past decisions. Neo4j is a graph database where graphs are natural, namely they are physically represented as a graph [10]. From an implementation perspective, a data structure which is efficient and versatile enough to store an implementation of the property graph, the conceptual model of Neo4j, is described in [18]. The Neo4j instance was interfacing with a Python client running the py2neo module, which allows both the formulation of dynamic Cypher queries and the delcarative manipulation of the database.

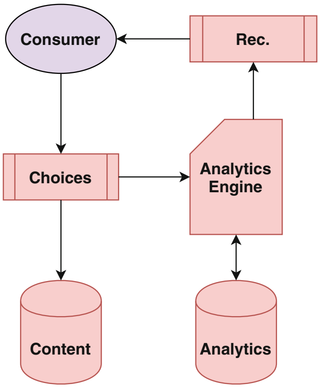

Fig. 1. Proposed analytics architecture.

3.2 Ties to Behavioral Economics and Cognitive Science

The recommendation architecture is explicitly or implicitly based on findings from behavioral economics and cognitive science. Also, it should be noted that the names of these findings are not unique as various studies may give them different names. The first finding establishes that a digital consumer is very likely to follow the recommendations. This is part justifies the frequent selections.

Proposition 1 (Default options). *A digital consumer is more likely to follow certain default options rather than change them.*

The second finding establishes that properly designed recommendations are likely to be relevant.

Proposition 2 (Sliding window). *There is a limited selection window where the preferences of the digital consumer remain constant.*

The third finding justifies the inclusion of past selections to the recommedations list as well as suggestions which are similar to past selections.

Proposition 3 (Cognitive bias). *A consumer will tend to select content she/he agrees with.*

3.3 Analytics

The first task is to define the entities, which in the graph database world are usually but not exclusively modeled as vertices, as well as the possible connections between them, which frequently form the edges. Here it should be noted that representing connections as vertices may sound counterintuitive, but within a graph database design context may well make sense.

For the purposes of this work, the following entities are considered:

– Digital consumers, which often are individuals but may well represent institution accounts, company accounts, or intelligent agents. Currently, they have the following properties: *name*, which is the unique vertex name, *hist*, which contains the last n content selections of the particular consumer, and *kw*, which is an array of at least three of the prespecified keywords of the right column of Table 2.
– Cultural content, which may well assume any form such as text, video, or music. Currently, they are composed of the following properties: *id*, which is the unique vertex id, and *kw*, which contains the keywords related to that verex.

How content simialrity can be quantified? A first approach is to compute the Tanimoto similarity coefficient between two content vertices and to insert a unique edge labeled SIMILAR with the actual coefficient value being a single edge property. Recall that said coefficient is defined as:

$$\tau\left(S_1, S_2\right) \triangleq \frac{\left|S_1 \cap S_2\right|}{\left|S_1 \cup S_2\right|} = \frac{\left|S_1 \cap S_2\right|}{\left|S_1\right| + \left|S_2\right| - \left|S_1 \cap S_2\right|} \tag{1}$$

An alternative approch relies on semantics and mapping sets to distributions. Specifically, each aspect keyword in the list of a content vertex is connected to a fundamental content type, as shown in Table 2. Consider, for instance, the following (fictional) keyword list:

$$\left[{'lyrics'}, {'music'}, {'opera'}, {'director'}, {'singer'}, {'actor'}, {'author'}\right] \tag{2}$$

Given the entries of Table 2, then the corresponding distribution is:

$$\mathbf{d} \triangleq \left[\frac{4}{7}, \frac{1}{7}, \frac{2}{7}\right] \tag{3}$$

The above distribution was derived by dividing the number of keywords from each category of Table 2 (in the order they are shown) to the total number of keywords in the list. Also, observe that each keyword has been selected on purpose to represent a specific aspect of the content type. Thus, aspect-specific analytics can be constructed as well. Moreover, each keyword has been assigned to only one category in order to avoid ambiguity. Once two distributions are given, their proximity can be computed using the cosine similarity:

$$c\left(\mathbf{d_1}, \mathbf{d_2}\right) \triangleq \frac{\sum_{i=1}^{p} \mathbf{d_1}\left[i\right] \mathbf{d_2}\left[i\right]}{\left(\sum_{i=1}^{p} \mathbf{d_1}\left[i\right]\right)^{\frac{1}{2}} \left(\sum_{i=1}^{p} \mathbf{d_2}\left[i\right]\right)^{\frac{1}{2}}} \tag{4}$$

Table 2. Keyword map to fundamental types.

Type	Keywords
Music	lyrics, opera, singer, instruments, soprano, music
Literature	author, structure, ending, plot, twist, literature
Theater	actor, director, lighting, performance, script, theater

In order to create a digital consumer vertex the following Cypher query should be used. Notice that every Cypher query must return a result, in this case the newly created vertex. Also, the **merge** clause ensures that at most one unique vertex is create, as if for some reason a duplicate vertex is attempted to be inserted, then no new vertex will be added to the graph. On the other hand, in such a scenario the **create** clause would have created a duplicate vertex.

```
merge (dc:consumer, {name: '<name>' ,
    hist: ['<ccid_1>', ..., '<ccid_n>'] ,
    kw: ['<kw_1>', ..., '<kw_n>']})
return dc
```

The following Cypher constraint ensures that the property *name* of a vertex of a type *consumer* is unique:

```
create constraint on (dc:consumer)
assert dc.name is unique
```

Having ensured the uniqueness of each consumer, the next query returns a list of all consumers in the system:

```
match (dc:consumer)
return dc.name as name order by name
```

Moreover, when a digital consumer accesses a certain piece of cultural content, then an ACCESS relationship is additionally created to indicate a generic access type with the *hits* property set to one. The **merge** clause is used as a safeguard against inserting multiple access relationships between the same pair of vertices.

```
match (dc:consumer {name:'name'}),(cc:content {id:'id'})
merge (dc)-[r:ACCESS {hits: 1}]->(cc)
return r as edge
```

On the contrary, when this is not the first time the consumer asks for this content, then the *hits* property can be updated like this:

```
match (dc:consumer)-[r:ACCESS]->(cc:content)
where dc.name='name' and cc.id='id'
set r.hits = r.hits + 1
return r.hits as hits
```

To access all the distinct cultural content a specific consumer with a given name has ever accessed it suffices that the following query is issued:

```
match (dc:consumer)-[:ACCESS]->(cc:content)
where dc.name = 'name'
return distinct(cc.id)
```

In this case the label ACCESS is used as it is not important whether the consumer was interested on the content as a whole or focused on specific aspects thereof.

Likewise, to find the top consumers having accessed the most unique cultural content, it suffices to run this Cypher query:

```
match (dc:consumer)-[:ACCESS]->(cc:content)
return dc as account, count(distinct(cc)) as amount
limit p
```

Counting all the hits a consumer has ever done up to this point can be performed in the following way:

```
match (dc:consumer)-[r:ACCESS]->(cc:content)
where dc.name = 'name'
with distinct(r) as rel
return sum(rel.hits)
```

The second group of graph cultural analytics dels with aspects of cultural vertrices. For instance, in a vertex about opera, one consumer may be particularly interested in the composer, one in the lyrics, and a third one in the year it was composed. Assuming that these aspects have been appropriately codified as a keyword in the *kw* property array of the respective vertex, then in addition the following relationship is created when the specific aspect is accessed for the first time:

```
match (dc:consumer)-[:ACCESS]->(cc:content)
where dc.name = 'name' and cc.id = 'id'
merge (dc)-[r:ASPECT::'<aspect>' {hits: 1}]->(cc)
return r
```

The above query raises the following three major architectural questions:

- When should a ASPECT::<aspect> be added or updated? We believe that the safest point to do is right after the corresponding ACCESS relationship has been added or updated. Even then an aspect is explicitly requested, again the ACCESS should be processed first.
- Should there be a distinct ASPECT::<aspect> relationship or just the generic ACCESS enriched with independent counting for each aspect request? We believe that separating the ACCESS relationship will provide for faster analytics, since separate counting process can collect in parallel the ACCESS and the relationship is additionally ASPECT::<relationship> relationships for all consumers. Moreover, seeking an aspect is semantically a different search from that of asking for the entire content.

- Along a similar line of reasoning, should there be a separate and dedicated ASPECT::<aspect> for each aspect or an array property in a generic ASPECT property along with a two-dimensional key-value array containing the aspects accessed so far and their respective hits? Extending our previous argument, we believe that Neo4j is primarily about handling relationships. Thus, respecting this fundamental design decision, our analytics will be more efficient, especially when computing values dependent on multiple aspects for all consumers. Additionally, the analytics can be written more naturally requiring less maintenance by taking advantage of the dynamic query formulation offered by py2neo.

The third and arguably more significant group of analytis deals with predicting the next cultural content request from a given digital consumer. Notice that the analytics themselves cannot be directly computed with Cypher queries, but they rely heavily on data collected by them. The one standing out is compiling a short personalized recommendation list for all digital consumers.

Here is presented an adaptive recommendation system combining past choices of the same consumer and similar content. The recommendations are updated after every decision, which in the long term yields statistically sound results. The list consists of $q_0 \equiv 0 \pmod 2$ suggestions, which was six in our senarios

- Out of them half were the most frequently accessed vertices in the t_0 decision past the current one, which in our case was three decisions ago. This small number not only saves memory space but it also consistent with the fact that a consumer will look for similar material over a short time window. These constitute sublist Q_p.
- The other half consists of the most similar vertices based on the vertices the consumer has seen so far excluding vertices already seen. These constitute sublist Q_n, which represents the novelty factor of the system.

The top half is selected adaptively based on the decisions the consumer has made in the recent past: If more options were from past options, then Q_p is the top of the list followed by Q_n, otherwise it is *vice versa*.

The Cypher queries for the verices representing cultural content are the same *mutatis mutandis*. For instance, along a similar line of reasoning, a cultural content vertex is created using this Cypher query:

```
merge (cc:content, {id: '<id>', kw: ['<kw_1>', ...]})
return cc
```

Finally, to clear the entire dataset the following Cypher query can be issued:

```
match (v) detach delete v
```

Note that the above query is inefficient for large datasets, practically when the order of vertices exceeds a few thousands.

3.4 Implicit Adjacency Tensor Format

Since each edge of the analytics graph, namely the graph stored at the database, is mandatorily labeled and there are multiple possible labels, it follows that said graph is by definition a multilayer graph as defined in [11]. This type of graphs can be represented with adjacency tensors, which are direct generalizations of the adjacency matrices for simple graphs. Such a tensor $\mathcal{T}$ is defined as in Eq. (5) where n is the total number of vertices and e is the total number of edges:

$$\mathcal{T} \in \{0,1\}^{n \times n \times e} \tag{5}$$

Specifically, the element $\mathcal{T}[v_i, v_k, l_j]$ where $1 \leq i, j \leq n$ and $1 \leq k \leq e$ equals one if and only if there is an edge with label l_k from v_i to v_j. Otherwise, it equals zero.

Notice that within the context of this work the adjacency tensor $\mathcal{T}$ is never explicitly constructed as it is never required, thus saving computational time. Nonetheless, the partitions of $\mathcal{T}$ are of great interest, since they reveal underlying connectivity patterns. A tensor layer can be obtained by fixing one of the three indexing integers. By focusing on the last integer, each resulting layer corresponds to an adjacency matrix formed by considering only a specific edge label. This yields two seprate cases.

Assuming there are n_d consumer and n_c content vertices with $n = n_d + n_c$ and also that the consumer vertices are all placed in $\mathcal{T}$ before the content ones, then a layer with consumer-to-content analytics has the form:

$$\mathcal{T}[:,:,k] = \left[\begin{array}{c|c} \mathbf{O}_{n_d,n_d} & \mathbf{A}_k \\ \hline \mathbf{O}_{n_c,n_d} & \mathbf{O}_{n_c,n_c} \end{array}\right], \quad \mathbf{A}_k \in \{0,1\}^{n_d \times n_c} \tag{6}$$

This layer, which is an adjacency matrix on its own right, corresponds to a special case of directed bipartite graph where the edge tails belong only to the consumer vertex set, denoted by V_d, and the edge heads belong only to the content vertext set, denoted by V_c. This is expected as only form of communication is that of a vertex $v_d \in V_d$ reaching one or more vertices of V_c. In this case, the maximum possible layer density happens when $\mathbf{A}_k$ has non-zero entries and equals:

$$\rho_0 \leq \frac{n_d n_c}{n^2} = \frac{n_d(n-n_d)}{n^2} = \frac{n_d}{n} - \left(\frac{n_d}{n}\right)^2 = \frac{n_d}{n}\left(1 - \frac{n_d}{n}\right) \tag{7}$$

On the other hand, when the analytics are content-to-content, then the respective layer has the form:

$$\mathcal{T}[:,:,k] = \left[\begin{array}{c|c} \mathbf{O}_{n_d,n_d} & \mathbf{O}_{n_d,n_c} \\ \hline \mathbf{O}_{n_c,n_d} & \mathbf{B}_k \end{array}\right], \quad \mathbf{B}_k \in \{0,1\}^{n_c \times n_c} \tag{8}$$

In these layers, matrices $\mathbf{B}_k$ represent the dynamic arising from connectivity patterns only between vertex pairs of V_c. In this case, the density ρ_0 of each layer is at most:

$$\rho_0 \leq \frac{n_c^2}{n^2} = \left(\frac{n_c}{n}\right)^2 \tag{9}$$

4 Results

4.1 Dataset

In order to evaluate in the *proof of concept* stage the proposed cultural analytics, a synthetic dataset has been created based on the preferences and features of real-world datasets about literature, opera, and theater. There are ten thousand requests in total from two thousand cultural consumers about nine hundred cultual vertices, with the three types of content being equally represented. Each request is a tuple of the form, where there may be up to three optional features:

$$(\text{consumer}, \text{vertex}[, \text{aspect}_1, \text{aspect}_2, \text{aspect}_3]) \tag{10}$$

The request distribution for each of three content types was Zipf with exponents in the rage of [2,3] in order to ensure that the distributions were converging both in the mean value and in variance. The Zipf distribution models many human-derived activities such as the letter frequency of words in natural languages, voting [6], and synthetic music generation [22].

As a baseline, four feedforward neural networks (FFNNs) have been chosen whose respective configurations are shown in Table 3. In this table each tuple entry corresponds to the total number of neurons of that given layer, whereas the number of entries is the number of layers. Always the first and the last layers are the input and output ones respectively, whereas any intermediate layers are hidden ones places in the order they are written. Layers are fully connected with each other, whereas the biases and the synaptic weights are randomly initialized.

Table 3. Configurations of the FFNN.

Name	FFNN1	FFNN2	FFNN3	FFNN4
Structure	8:8:1	8:4:1	8:8:1	8:4:1

Each such network is fed a sequence of content vertex ids and the final output of an FFNN is alao such an id. In each hidden layer the activation function is the parametric SoftPlus function $\varphi_f(\cdot)$, which is a smooth approximation to the ubiquitous ReLU function and additionally has the desired leaky property which avoids synaptic weight saturation. It is defined as:

$$\varphi_f(u; \alpha_0, \beta_0) \triangleq \ln\left(1 + \exp\left(\alpha_0 u + \beta_0\right)\right) \tag{11}$$

The activation function at the output layer neuron for the configurations FFNN1 and FFNN2 is the parametric sigmoid function $\varphi_s(\cdot)$:

$$\varphi_s(u; \alpha_0, \beta_0) \triangleq \frac{1}{1 + \exp\left(-\alpha_0 u + \beta_0\right)} \tag{12}$$

For the configurations FFNN3 and FFNN4 the activation function is the hyperbolic tangent function $\varphi_t(\cdot)$:

$$\varphi_t(u; \alpha_0, \beta_0) \triangleq \alpha_0 \tanh\left(\beta_0 u\right) \tag{13}$$

4.2 Accuracy

Table 4 lists the accuracy of the proposed methodology with either the Tanimoto similarity coefficient (P1) or the cosine similarity coefficient (P2). From the results it can be seen that P2 achieves slightly better accuracy than P1. This can be attributed, partly at least, to the fact that P2 is based on a semantically aware method, even an indirect one. On the other hand, P1 is semantically oblivious, reducing the real semantic question to a set similarity problem and in turn to a mere matching problem.

Table 4. Accuracy for the next content selection.

Method	P1	P2	FFNN1	FFNN2	FFNN3	FFNN4
Accuracy (%)	87.33	89.15	79.94	81.48	82.41	84.72

5 Conclusions and Future Work

This conference paper presented a batch of fundamental graph analytics for cultural content recommendation expressed in the form of Neo4j Cypher queries. The latter are based not only on the past decisions of a specific digital consumer, as frequent selections within a certain window, but also on content similarity metrics. The latter rely on a set of keywords describing the aspects of other main properties of the specific piece of cultural content. On that set either a semantically oblivious or a semantically aware similarity metric can be applied in order to yield the final list of recommendations. Early results from a synthetic dataset indicate that the semantically aware similarity metric yields better results in terms of the prediction accuracy. Moreover, both methods outperform a baseline consisting of four configurations of a basic feedforward neural network. Thus, the proposed methodology can offer both better accuracy and interpretability, something neural networks typically lack.

Currently the proposed methodology considers a number of consumer-to-content or content-to-content analytics only. Therefore, the addition of consumer-to-consumer analytics would be a significant addition, since various clusterings of the digital consumer set may yield improved recommedations based on the preferences of similar consumers. Moreover, time is going only forward and as a consequence no rollback methods are available to face possible system anomalies. Finaly, another direction worth exploring is incorporating semantics into possible consumer set similarity metrics, provided such a move has a meaning.

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