

Metrics for Objective Ontology Evaluations

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Abstract: We present new metrics and techniques which allow one to configure a metadata catalogue and objectively describe knowledge management ontologies. Per C.E. Shannon (1948), when describing information based systems, statistical measures are a necessity; yet very few ontology based standards mention quantifiable measures such as entropy, data encapsulation, complexity, efficiency, evolution, or redundancy. We hope to demonstrate how statistical information measures can be implemented for ontology-based knowledge management systems using our L_0 statistic, entropy, evolution, organization, sensitivity, and an interpretation of complexity.

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Lecture Rules

- Feel free to stop me at any time. I mean it.
- If you have a question, then ask it.
- Feel free to leave any time you want. You will not hurt my feelings.
- Please shut your mobile phone off or silence the ringer now.
- If you wish to contact me, go to www.pefferly.com for e-mail/phone.
- I apologize in advance for breaking the cardinal rule of slides.
- If something is indented and attributed to an author.... It is a quote.

Who are the authors?

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Motivation + Innovation

Thus, the crux of any knowledge system is the information content and knowledge encapsulation that maximizes the sufficiency of the metadata; not in whether an ontology is subjectively 'linguistically correct' or follows 'common sense.'

An ontology is a collection of symbols used to express data ... they are structurally nothing more complex than a finite set of symbols with a bijective mapping.

The power of an ontology is that it embraces chaos and does not define or impose an a priori structure, unlike a data base. It approaches Shannon optimal coding in that redundancy is reduced and recognises that information is fluid and not static.

The true innovation of this paper lies in the informatic metrics we prescribe for describing/comparing complex ontology based systems. We hope to demonstrate how objective statistical information measures can be implemented for objective knowledge management - one can now compare ontologies and answer the question: 'Is one ontology better than another?'

How to use objective metrics?

1

- **Building Stage**
- Instead of spending one year of a project developing an ontology, maybe only six months was substantially beneficial for effective information content. Points of diminishing returns can be identified and resources reallocated appropriately.
- One can finalize an iterative building process once the recommended changes add less than 'X' value to the knowledge management.
- **Manipulating Stage**
- The question of 'Is one ontology more effective than another?' can be objectively evaluated.
- How does one determine if the 'coverage' of an ontology is sufficient?
- What is the value added when changing elements in an ontology?

How to use objective metrics?

2

- **Maintaining Stage**
- 'Is one ontology easier to maintain than another?' can be addressed.
- What does the addition or elimination of term 'X' do to the system? Will there be unintended consequences?
- **General:** An iteration of domain expert solicitation must occur, but it is difficult to measure progress - organizations must address issues such as:
- What is the value added with each iteration?
- When manipulating ontologies, how does one demonstrate improvement?
- When changing the terminology or structure of an ontology, how does one demonstrate the change is either beneficial, detrimental, or futile + moot?
- When maintaining an ontology, when does the redundancy and complexity become prohibitive?

New Metrics

Inspired by Claude Shannon and Francis Hildebrand

$$\mathbb{L}_0(F(X)) = \mathbb{E} \left[\sqrt{\frac{\mathbb{P}(j)}{\text{card}(\mathcal{U})}} \right]^{-1}$$
$$= \frac{1}{\sum_{j=1}^N \mathbb{P}(j) \sqrt{\frac{\mathbb{P}(j)}{\text{card}(\mathcal{U})}}}$$

- The $\mathbb{L}_0$ statistical complexity is defined by the inverse of the expectation where non-zero probability elements comprises domain space.
- As discussed by C.E. Shannon a uniform distribution is optimal for information content, thus our complexity statistic is based on the Discrete Uniform Probability Distribution and has a lower bound of 0 with an unlimited upper bound.
- “Information mass”

New Metrics

2

$$\Phi(F(X)) = \mathbb{E}(\mathbb{P}(F(X))) = \sum_{j=1}^N \mathbb{P}^2(j)$$

$$\mathcal{E}(F(X)) = \Phi(F(X))^{-1}$$

- The organization or structure of a process-ontology.
- Sometimes referred to as an envelope.
- The evolution of a process where simple structure indicates that a system is highly organized and the more organized a system is, the smaller its evolution.
- The difference between two ontology evolution values represent a measure of informatic distance.

New Metrics

3

$$\begin{aligned}\mathcal{S}(F_N(X)) &= \Delta \mathcal{E}(F_N(X)) \\ &= \mathcal{E}(F_{N \pm 1}(Y)) - \mathcal{E}(F_N(X))\end{aligned}$$

where $\text{card}(F_N) = N$

and $\text{card}(F_{N \pm 1}) = N \pm 1$.

- The sensitivity is a first order difference (change) in the evolution of a system when an element is either eliminated (or added) from the process.
- Sensitivity will be a measure similar to the sensitivity of a numerical approximation, in that it will be a measure of the effect a small change in the structure has on the overall system.
- For our purposes, sensitivity will be measured as a finite difference of the organization metric via the addition/deletion of a term.

Example – a six sided die

- **Theoretical die**

- The physical phenomena of rolling a six sided equiprobable die.
- Discrete space where each side has a one in six chance of appearing.
- The expected value is 3.5 and variance is $2 \frac{11}{12}$.
- Optimal coding with 0 redundancy.

- **Bayesian die**

- Assume that the six sided die is 'too complex' for one to understand.
- Roll the die 10 times and plot the histogram of the data.
- Results: { 3,1,6,6,4,5,2,3,6,5 }.
- Sample mean is 4.1 and the sample variance is 3.211.

Example – simple ontology

- **Theoretical Ontology**

- A six term ontology is designed by a knowledge engineer/expert who estimates a priori probability values for filling data elements.

Element (x)	$\mathbb{P}(x)$
Version	$\frac{1}{20}$
Summary	$\frac{1}{20}$
Organization	$\frac{3}{20}$
Date	$\frac{4}{20}$
Author	$\frac{5}{20}$
Title	$\frac{6}{20}$

Table 2: A priori ontology

- **Bayesian Ontology**

- The same ontology is utilized where Bayesian a posterior probabilities are derived from 'real instances' stored in the catalogue.

Element (x)	M1	M2	M3	M4	M5	$\mathbb{P}(x)$
Version		X				$\frac{1}{18}$
Summary				X		$\frac{1}{18}$
Organization	X	X		X		$\frac{3}{18}$
Date	X	X	X	X		$\frac{4}{18}$
Author	X		X	X	X	$\frac{4}{18}$
Title	X	X	X	X	X	$\frac{5}{18}$

Table 3: A posterior ontology

Results

Metric	Theoretical die	Bayesian die	A priori ontology	Bayesian ontology
$\mathcal{H}$	0.778	0.736	0.7009	0.714
$\mathcal{H}_{Rel}$	1	0.946	0.9007	0.9176
$\mathcal{R}$	0	0.0536	0.0993	0.0824
$\mathcal{O}$	6	6	6	6
$\mathbb{L}_0$	6	5.592	5.334	5.442
Φ	0.1667	0.2	0.22	0.2099
$\mathcal{E}$	6	5	4.545	4.765
$\mathcal{S}$	-1	-0.736	-0.396	-0.451

Table 1: Metric results

Conclusion

Do an example right now?

Questions?

Thank you for your time and effort.