

# Spectral Analysis of Real Weighted Graphs

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Headline	Time
<b>Total time</b>	<b>8:31</b>
Tasks	8:31
Derive the Sigmoid Curve	4:00
Derive and explain the equation on...	4:31

Table 1: Clock summary at [2020-12-05 Sat 19:40]

Project Topic    *Spectral Analysis of Real Weighted Graphs*  
Adviser          Assoc. Prof. Laurence Park

```
1  zotero & disown
2  kitty -e 'cd /home/ryan/Sync/Studies/2020ResearchTraining/spectral_analysis_graphs/' &
   ↪ disown
3  mattermost & disown
```

## 1 Tasks

### 1.0.1 Derive the Sigmoid Curve

Just make sure that you understand logistic regression so there is a ground-truth classification method.

### 1.1 Derive and explain the equation on page 3

RankNet is concerned with ranking things, the most obvious application of this is information retrieval, for example if a search returns a variety of results that are very similar to the query they will need to be ordered in some way to make them more useful. This is traditionally done with *PageRank* or by simply using TF-IDF weighting, it is not immediately clear what advantages this approach has, presumably it ranks results better.

The output of Ranknet is concerned with a probability of one object being ranked higher than another and implements a Neural Network in order to model this. It is not clear why RankNet is used for this rather than traditional classification techniques.

Take two objects  $U_i, U_j$  (e.g. an article, document or anything else) that are described by a feature vector  $\mathbf{X}_i$  and  $\mathbf{X}_j$ . RankNet maps this feature vector to some number:

$$f : \mathbb{R}^n \rightarrow \mathbb{R} : \mathbf{X} \mapsto s$$

If  $U_i$  is ranked higher than  $U_j$  this is denoted by:

$$U_i \triangleright U_j$$

The two outputs  $(s_i, s_j)$  are mapped to a probability that  $U_i$  is ranked higher than  $U_j$  via a sigmoid function:

## 1.1 Derive and explain the equation on page 3

$$p_{ij} \equiv P(U_i \succ U_j) \equiv \frac{1}{1 + e^{-\sigma(s_i - s_j)}}$$

The model is dependent on the  $\sigma$  value as shown in figure ??.

[media/sigmoid\\_animation.gif](#)

In order to fit this curve a penalty term needs to be introduced to measure how well the curve fits the data. In regression analysis ( $\text{RMSE} = \sqrt{\sum_{i=1}^n [(x_i - \hat{x})^2]}$ ) is often used and could be implemented here.

Assume this is a binary classification problem (i.e. they won't match ranks) and let  $p$  describe the probability of an object belonging to class 1. If an observation belongs to class 1 we can measure the *badness of fit* by  $1 - p$ , conversely if an object truly belongs to class 0 we can measure the badness of fit by  $p$ , this is illustrated in figure 1.

Actual Class	Residual	Cost
$p = 0$	$p$	$\ln \frac{1}{1-p}$
$p = 1$	$1 - p$	$\ln \frac{1}{p}$
Either	$p^{(1-\bar{p})} \cdot (1-p)^{\bar{p}}$	$\ln \left( p^{-p} \cdot (1-p)^{-(\bar{p}-1)} \right)$

Table 2: Residuals and costs function for

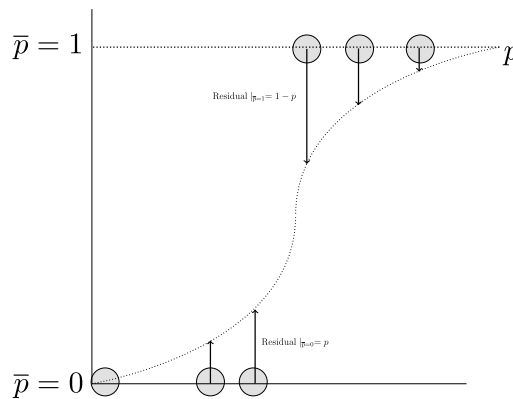


Figure 1: Residual from Classified points

These residuals could be combined to account for either situation:

$$C = p^{1-\bar{p}} \cdot (1-p)^{\bar{p}} \quad (1)$$

A log transform would give a more convenient function (i.e. no exponents), because the transform is monotone this will still work as a cost function and so this could be implemented:

$$C = (1 - \bar{p}) \cdot \ln(p) + \bar{p} \cdot \ln(1 - p) \quad (2)$$

This however is not implemented, instead the cost functions implemented correspond to table 2, presumably this is due to the fact that this cost function performs well:

$$e^C = P_{ij}^{-\bar{P}_{ij}} \cdot (1 - P_{ij})^{(\bar{P}_{ij}-1)} \quad (3)$$

$$\implies C = -\bar{P}_{ij} \ln(P_{ij}) - (1 - \bar{P}_{ij}) \ln(1 - P_{ij}) \quad (4)$$

Let the actual status of the ranking be defined by  $S_{i,j} \in \{-1, 0, 1\}$  like so:

$S_{ij}$	Status
1	$U_i \succ U_j$
-1	$U_i \triangleleft U_j$
0	$U_i \square U_j$

This provides that:

$$\bar{P}_{ij} = \frac{1}{2} (1 + S_{ij}) \quad (5)$$

c=1; p = 0.7; L(x) = 1-p  
 c=0; p = 0.7; L(x) = p  
 p^c \* (1-p)^(1-c)

$$p^c (1 - p)^{(1-c)}$$

It is however more convenient to log transform this, a log transform is monotone and so we can still use it as a loss function. so we are dealing with sums and products rather than exponentials:

$$\log(p^c (1 - p)^{(1-c)}) = \dots$$

The equation on page 3 we get by plugging in the the preceeding two equations (value of p and value of  $\bar{p}$ )

## 1.2 Watch and summarise the Neural Networks Video

Create a Citation for this: [RankNet/RankNet\\_To\\_LambdaRank.pdf](#)

## 1.3 Create a Neural Network to Classify binary data

- Get the Data from UCI
- Use three softwares to get an idea for it:
  - [RTorch](#)
  - [pytorch](#)
  - [JuliaTorch?](#)

Compare the usability and performance of the different OS.

## 1.4 Set up a Wiki and put the working in there

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### 1.4 Set up a Wiki and put the working in there

And/or put the working into MkDocs Pages.

### 1.5 Set up the wiki and comment on Mattermost

### 1.6 Add to the CDRMS Repo

### 1.7 Set up Kanboard Page

Share that page with Laurence.

This means that  $U_i$  is ranked higher than  $U_j$

### 1.8 Derive the sigmoid function for logistic regression

### 1.9 Clarify the Question

*Is there any benefit to using Ranknet rather than simply using Classification?*

## 2 Ranknet

The Ranknet uses a [Sigmoid Curve](#) curve:

$$U_i \triangleright U_j$$

## 3 Summary

### 3.1 What is spectral Graph Theory

Spectral graph theory starts by associating matrices to graphs, mostly the:

- Adjacency Matrix
- Laplacian Matrix

### 3.2 What do we mean by real weighted graphs

Like non-integer values.

### 3.3 What do I want to look at researching

### 3.4 What is the Research Outline

#### 3.4.1 This is what I put together in Planner

## 4 Research

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#### 4.1 Research Papers

- Tu, E., Zhang, Y., Zhu, L., Yang, J., & Kasabov, N., A Graph-Based Semi-Supervised k Nearest-Neighbor Method for Nonlinear Manifold Distributed Data Classification (). [4]
  - PDF
- Chang, S. Y., Pierson, E., Koh, P. W., Gerardin, J., Redbird, B., Grusky, D., & Leskovec, J., Mobility network modeling explains higher SARS-CoV-2 infection rates among disadvantaged groups and informs reopening strategies (). [2]
  - PDF

#### 4.2 Books

- Bondy, J. A., & Murty, U. S. R., Graph theory with applications (), : North Holland. [1]
  - PDF (local, absolute path)
- Nicodemi, O., Sutherland, M. A., & Towsley, G. W., An introduction to abstract algebra with notes to the future teacher (), : Pearson Prentice Hall. [3]
  - Books on Spectral Graph Theory

### 5 Ring Theory

### ATTACH

A ring is a set that has two operations (see [3, §§2.4-2.6]):

- Addition (+)
- Multiplication  $\cdot$

And Satisfies the axioms of a ring:

#### 1. Associativity of Addition

$$(\forall a, b, c \in \mathcal{R}) (a + b) + c = a + (b + c)$$

#### 1. Commutativity of Addition

$$(\forall a, b \in \mathcal{R}) a + b = b + a$$

#### 2. Additive Elements Exist

$$(\forall a \in \mathcal{R}) \wedge (\exists_0 \in \mathcal{R}) a + 0 = 0 + a = a$$

#### 3. Additive Inverse Exists

$$(\forall a \in \mathcal{R}) \wedge (\exists b \in \mathcal{R}) a + b = b + a = 0$$

- This can be equivalently expressed:

## 5.1 Integral Domain

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$$(\forall a \in \mathcal{R}) \wedge (\exists (-a) \in \mathcal{R}) a + (-a) = (-a) + a = 0$$

### 4. Associativity of Multiplication

$$(\forall a, b, c, \in \mathcal{R}) (a \cdot b) \cdot c = a \cdot (b \cdot c)$$

### 1. Distributivity of Multiplication over Addition

- $(\forall a, b, c, \in \mathcal{R}) (a \cdot (b + c) = (a \cdot b) + (a \cdot c))$ , AND
- $(\forall a, b, c, \in \mathcal{R}) (a + b) \cdot c = (a \cdot c) + (b \cdot c)$

### 5.0.1 Further Axioms

Other conditions to have special classes of rings exist:

#### 1. Commutativity of Multiplication

- A ring that satisfies this property is called a **commutative ring**  
 $(\forall a, b \in \mathcal{R}) a \cdot b = b \cdot a$

#### 2. Existence of a Multiplicative Identity Element (A ring with Unity)

- A ring that satisfies this property is called a **ring with identity** or

equivalently a **ring with unity** (the multiplicative identity, often denoted by 1, is called the **unity** of the ring.

$$(\exists 1 \in \mathcal{R}) (\forall a \in \mathcal{R}) 1 \cdot a = a \cdot 1 = a$$

## 5.1 Integral Domain

An integral domain is a ring that:

1. is commutative
2. With identity/unity
3. Has no Zero Divisors

In an integral domain we can cancel values:

$$(c \neq 0) \wedge (ac = bc) \implies a = b$$

## 5.2 Fields

A field is:

1. An Integral Domain
2. In which every non-zero element is a unit

A unit in a ring is an element of a ring that always has a multiplicative identity.

## References

- [1] J. A. Bondy and U. S. R. Murty. *Graph Theory with Applications*. Includes index. New York: North Holland, 1976. 264 pp. ISBN: 978-0-444-19451-0 (cit. on p. 6).
- [2] Serina Y Chang et al. *Mobility Network Modeling Explains Higher SARS-CoV-2 Infection Rates among Disadvantaged Groups and Informs Reopening Strategies*. preprint. Epidemiology, June 17, 2020. DOI: [10.1101/2020.06.15.20131979](https://doi.org/10.1101/2020.06.15.20131979). URL: <http://medrxiv.org/lookup/doi/10.1101/2020.06.15.20131979> (visited on 12/02/2020) (cit. on p. 6).
- [3] Olympia Nicodemi, Melissa A. Sutherland, and Gary W. Towsley. *An Introduction to Abstract Algebra with Notes to the Future Teacher*. Includes bibliographic references (S. 391-394) and index. Upper Saddle River, NJ: Pearson Prentice Hall, 2007. 436 pp. ISBN: 978-0-13-101963-8 (cit. on p. 6).
- [4] Enmei Tu et al. *A Graph-Based Semi-Supervised  $k$  Nearest-Neighbor Method for Nonlinear Manifold Distributed Data Classification*. Comment: 32 pages, 12 figures, 7 tables. June 3, 2016. arXiv: [1606.00985](https://arxiv.org/abs/1606.00985) [cs, stat]. URL: <http://arxiv.org/abs/1606.00985> (visited on 12/02/2020) (cit. on p. 6).