Pattern Recognition 2017 Term Project

Damage Location Prediction for a Bridge using Machine Learning

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CONTENTS

Current Situation & Limitation of Bridge Management

- Have a difficulty with obtaining reliable data
  - Ambiguous criteria
  - Experts' opinions are dominant over precedent studies
  - Subjective assessment

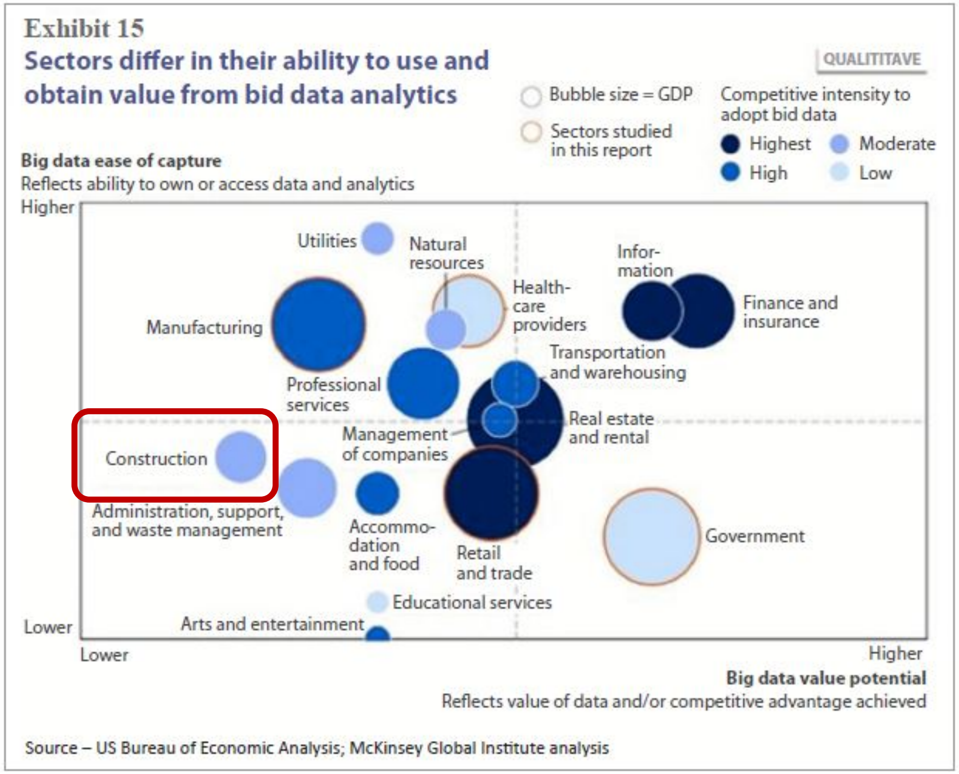
- Bridge management computer system supports only saving function
  - Lack of functions providing meaningful information

판정등급	상 태
A	• 발생된 손상이 경미하여 당장 보수를 요하지 않으나, 추적조사 후 보수여부를 결정해야 하는 상태
B	• 발생된 손상이 심각하지는 않으나, 상세하게 추적조사 후 보수해야 하는 상태
C	• 발생된 손상이 교량에 심각한 지장을 주지는 않지만, 빠른 시일 내에 보수해야 하는 상태
D	• 발생된 손상이 심각하지만, 별도의 응급조치는 필요없고 속히 보수해야 하는 상태
E	• 발생된 손상이 심각하여 먼저 통행제한과 응급조치를 한 후 바로 보수해야 하는 상태

Table 1. Criteria of bridge grade

Necessity of Planning Data Application

- A lot of old bridges outside of Seoul
- Inattention to follow up management
- Lower utilization of data in the field of Architecture and Civil engineering than other fields



Finance industry is highest ranking in terms of its ability to use and obtain value from big data.

Bridge Management System

Bridge Information Management System; BIMS

Bridge Information **Analysis** Management System; BIAS

Condition Prediction

Bridge grades
Material condition
By region

Expense Prediction

Repair
Reinforcement
Routine management
Risk cost

Decision Making

Budget allocation
Budget estimation
Repair time
Rebuilding priority

Research Objective

Challenging application to Architecture/ Civil engineering

Influence factors
for the bridge condition

Prediction

Damage Location

Continuous **A**cquisition & **L**ife-cycle **S**upport

- Architecture- CALS
  - Results of inspection for the bridge in Korea

- Inspection date range : 1995. 11.11 ~ 2015

- Contents of inspection
  - Bridge name
  - Location
  - Inspection date
  - Grade
  - Detail of damage
  - Size of damage
  - Follow up measure
  - Bridge structure
  - Etc.

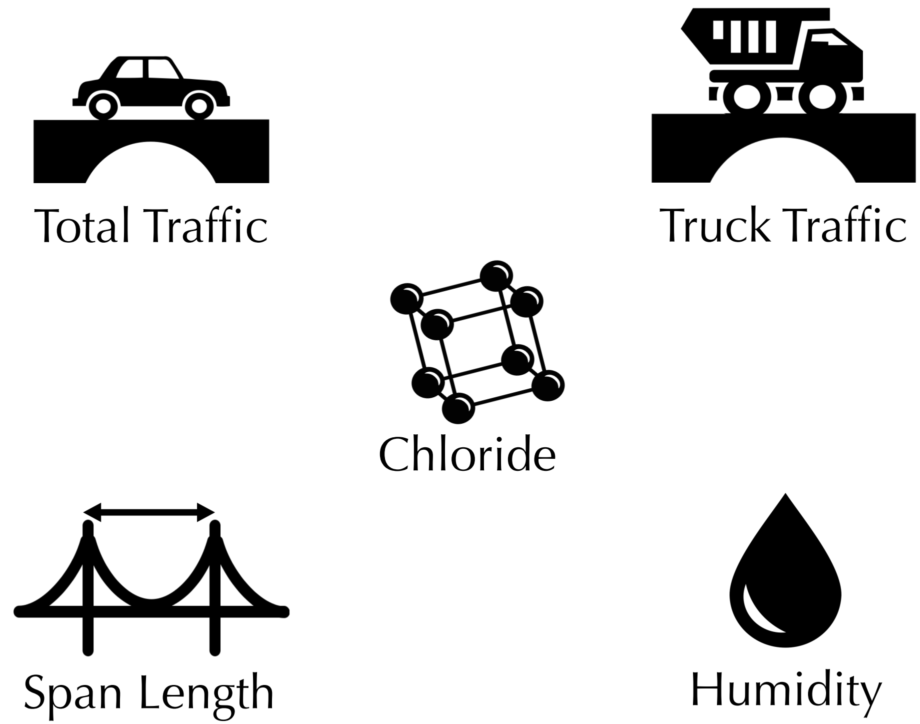
- About 50,000 bridges
  - Exclude samples having missing values

Influence Factors

		Whole bridges				Bridge elements		
Factors	*Jiang (1990)*	*Scherer and Glagola (1994)*	*Zhao and Chen (2002)*	*Su (2003)*	*Huang and Hsu (2005)*	*Morcous et al. (2002)*	*Huang (2003)*	*Chen (2005)*
General factors								
Bridge age		v	v	v		v		v
No. of spans		v	v				v	
No. of lanes				v				v
Length of bridge			v	v		v	v	v
Area/width of deck			v			v	v	v
Max. span				v				
Skew angle						v		
Structural factors								
Structural type	v		v	v		v		v
Girder type				v		v		v
Girder material		v				v		
Abutment type				v				
Pavement				v		v		
Earthquake bracing				v				
Expansion joint								v
Wing wall				v				
Designed live load							v	v
Traffic factors								
Traffic volume	v	v				v	v	v
Environmental factors								
Over water or not?				v	v		v	
Distance from coast				v	v			v
Acid rain								v
Avg. yearly rainfall		v			v			
Avg. rainy days per year								v
Soil profile					v		v	
Others								
Road level	v	v				v		
Climate region	v				v	v		

Table 2. Influence factors from precedent foreign studies

Features


Total Traffic
Truck Traffic
Chloride
Span Length
Humidity

Classes

- Damage Locations

1. Floor beam
2. Bridge pier
3. Bridge bearings
4. Pavement
5. Rail curve
6. Floor slab
7. Drainage
8. Expansion joint
9. Mold

Two most common damage locations

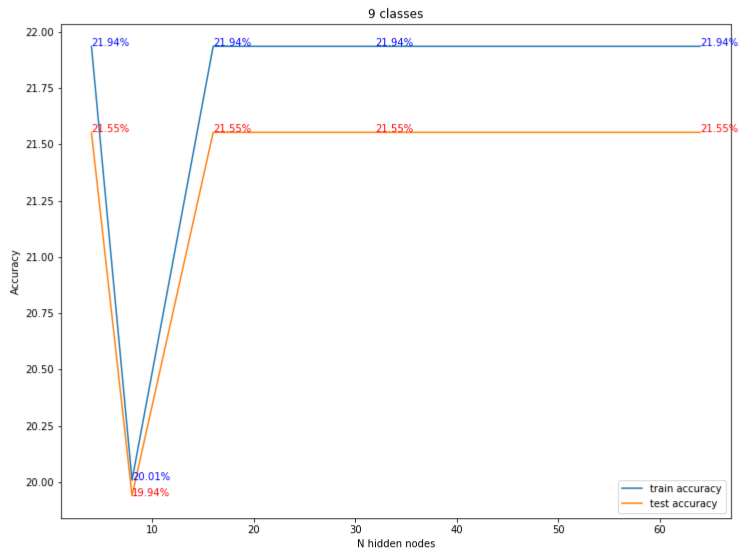
Methods

- Multi Layer Perceptron (MLP)
  - A feedforward artificial neural network model
- Support Vector Machine (SVM)
  - Kernel based model constructing a hyperplane in a high dimensional space
- Decision Tree (DT)
  - Tree-like model
- Gaussian Naïve Bayes (GNB)
  - Simple probabilistic classifier based on applying Bayes' Theorem with strong independence assumptions

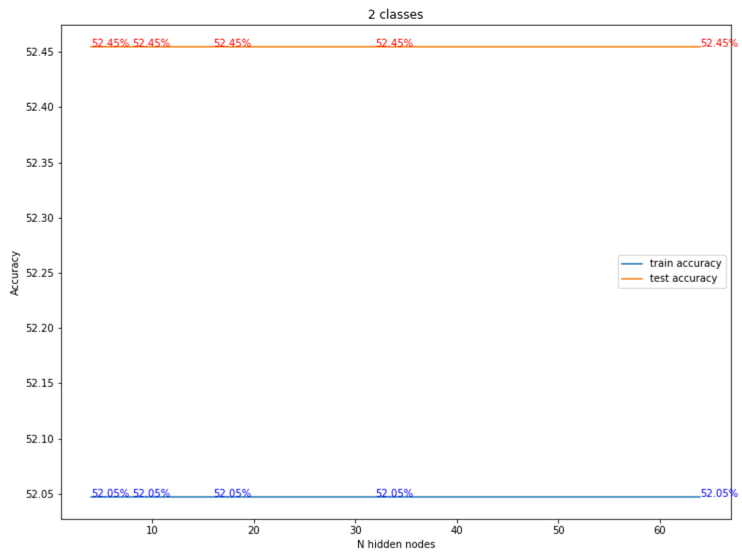
Test

- 5 Fold Cross Validation

Results - MLP



- 9 class
  - 21.55%



- 2 class
  - Rail curve
  - Floor slab
  - 52.45%

Results
- SVM
- 9 classes

- **Linear kernel**

C (penalty)	CV1	CV2	CV3	CV4	CV5	MEAN
0.1	0.08	0.09	0.13	0.06	0.06	0.08
1	0.13	0.16	0.06	0.12	0.08	0.11
10	0.14	0.13	0.12	0.1	0.14	0.12
100	0.17	0.16	0.13	0.15	0.18	0.15

- **Radial Basis Function kernel** (Gamma = 0.7)

C (penalty)	CV1	CV2	CV3	CV4	CV5	MEAN
0.1	0.18	0.18	0.18	0.18	0.18	0.18
1	0.18	0.19	0.19	0.19	0.18	0.19
10	0.17	0.17	0.16	0.13	0.14	0.15
100	0.13	0.20	0.21	0.20	0.18	0.18

  - Tried Gamma 0.2 as well

- **Polynomial kernel**
  - Tried degree 2, 3 and 5
  - Similar accuracy with RBF kernel

Results
- SVM
- 2 classes

- **Linear kernel**

C (penalty)	CV1	CV2	CV3	CV4	CV5	MEAN
0.1	0.66	0.66	0.65	0.68	0.68	0.67
1	0.62	0.48	0.65	0.31	0.32	0.47
10	0.67	0.66	0.35	0.52	0.63	0.57
100	0.61	0.66	0.6	0.68	0.36	0.58

- **Radial Basis Function kernel** (Gamma = 0.7)

C (penalty)	CV1	CV2	CV3	CV4	CV5	MEAN
0.1	0.76	0.77	0.77	0.77	0.78	0.83
1	0.82	0.81	0.82	0.82	0.83	0.84
10	0.82	0.81	0.82	0.81	0.83	0.84
100	0.82	0.81	0.82	0.81	0.83	0.84

  - Tried Gamma 0.2 as well

- **Polynomial kernel**
  - Tried degree 2, 3 and 9
  - About 60% test accuracy

Results

- Plot the decision surface
- Consider only 2 features: truck traffic and Chloride

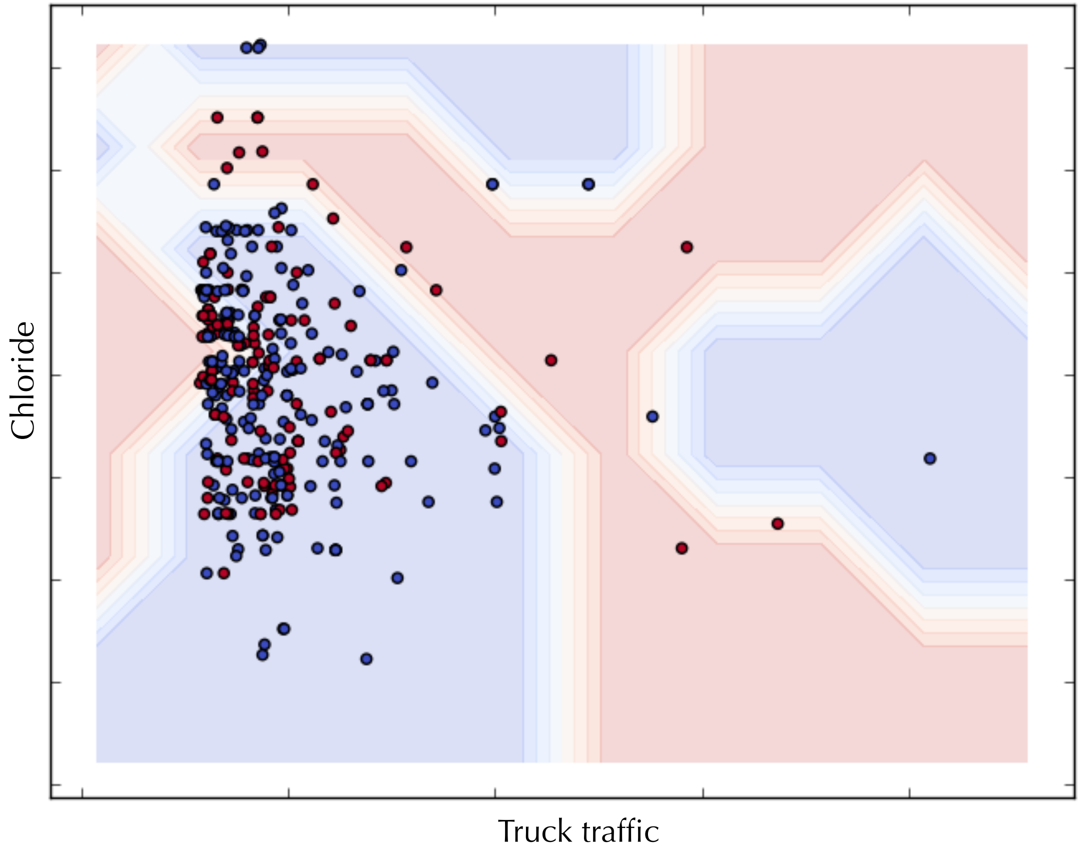


Figure 2. Decision surface for SVM classifier with RBF kernel

Results
- DT
- GNB

- **Decision Tree**

Class	CV1	CV2	CV3	CV4	CV5	MEAN
2	0.57	0.66	0.75	0.42	0.63	0.62
9	0.08	0.16	0.19	0.12	0.2	0.17

- **Gaussian Naïve Bayes**

Class	CV1	CV2	CV3	CV4	CV5	MEAN
2	0.53	0.62	0.55	0.74	0.63	0.68
9	0.125	0.2	0.16	0.16	0.07	0.17

Results
- Summary

- With 2 classes, SVM shows higher accuracy than MLP while MLP shows higher accuracy than SVM
  - Neural net model is effective when the number of class is large
- SVM with RBF kernel have the highest accuracy among SVM with other kernels

- 9 class case
  MLP > RBF ≥ Polynomial ≥ DT ≥ GNB > Linear

- 2 class case
  RBF ≥ GNB ≥ Polynomial > Linear > DT> MLP

Limitations & Future works

- Absence of data like vibration which could represent the condition of bridge in direct
  - The extent of damage can be known from the vibration frequency
- Need to consider other formats of data to classify damage locations for the bridge
- Consideration of complex relations among factors

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Thank you