Travel Time Based on Vehicle Signatures

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TULSA CAMPUS

Outline

- Objectives
- Introduction
- System Architecture
- Data Collection Methodology
- Data Analysis
- Conclusion

Objectives

- To estimate the travel time on a route using vehicle magnetic signature sampled by inductive loops only.

- To investigate the feasibility of tracking trucks particularly and vehicles in general by identifying a unique features in per-vehicle magnetic signature.

Introduction – Travel Time (TT)

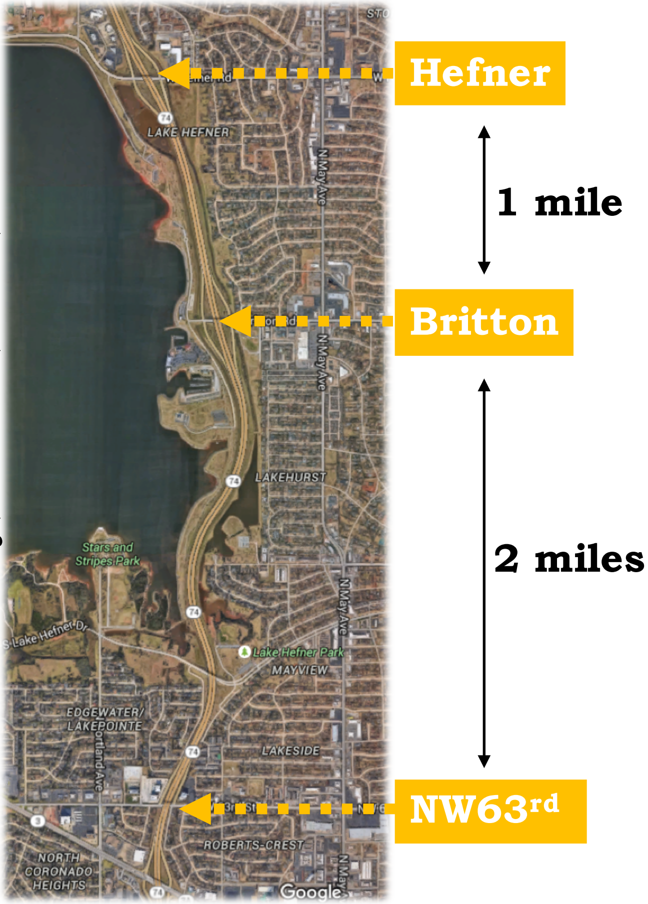
- TT is a reciprocal of average speed and can be defined as a measure of traffic congestion between two points on a road segment.
- TT has been identified as a time-based performance measure of transportation quality and level of service.
- An accurate and reliable TT information can help to reduce congestion, improve safety, and enhance traffic flow.
- Measuring TT requires speed estimation and vehicle re-identifying.
- Different technologies have been used by transportations agencies for making TT estimation including 1) Bluetooth and Wi-Fi identification detectors; 2) Toll tag reader; 3) in-pavement magnetic detectors; 4) automatic license plate readers; 5) machine vision; 6) radars; 7) crowdsourcing; and 8) cell phone signal monitoring.

Hardware System:

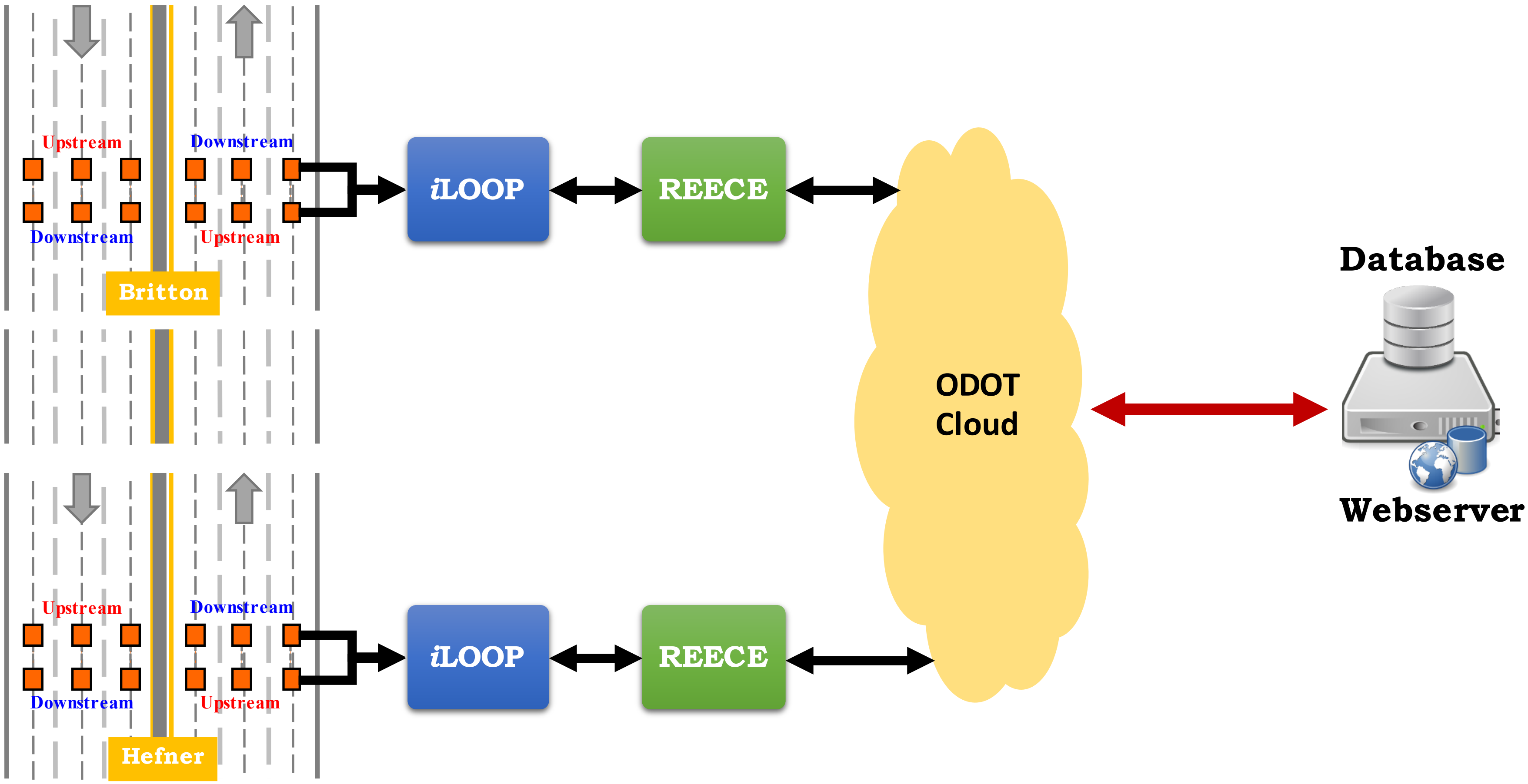
- Diamond Traffic Phoenix Classifier
- Loop only Classification equipment-- iLoop
- Uses Regular 6’ by 6’rectanglular inductive loops
- Vehicle classification based on inductive loop signatures
- Uses machine learning algorithms for training.
- Sends vehicle signature to fast RS-232 ports in real-time
- Sampling rate is 1KHz.

Experimental Setup

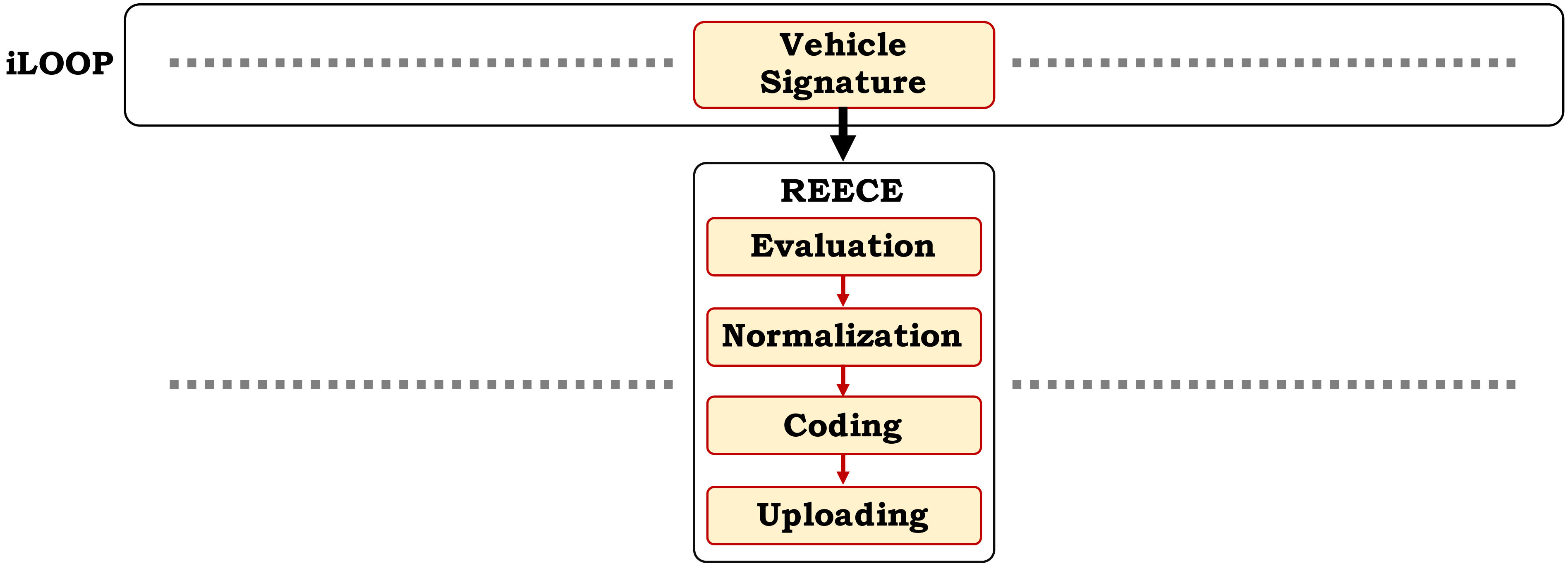
Lake Hefner Pkwy, U.S. 74, OKC, OK 73120



Data Collection Methodology



Data Collection Methodology



CODE: <Timestamp><Site><Lane><Encoded_Signature>

Data Analysis – Normalization

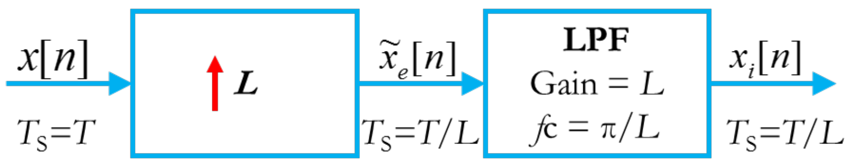
- Encoding vehicle signature requires a normalized signature (i.e., time and magnitude).
- If vehicle speed is known and accurate, signal length normalization can be achieved as a time-domain multiplication of signal length by speed and sampling time.

$$\tilde{x}_n = v.T_s.x_n$$

- The sampling rate used to sample vehicle magnetic signature during this test was 1kHz.
- The number of samples in vehicle signature is speed- and length-dependent, ranging in our collected dataset between 100 ~ 1000 samples at fs = 1kHz
- In case all signals should have same number of samples, interpolation and decimation processes can be applied to resample all vehicle signatures at predefined signal length.

Data Analysis – Normalization

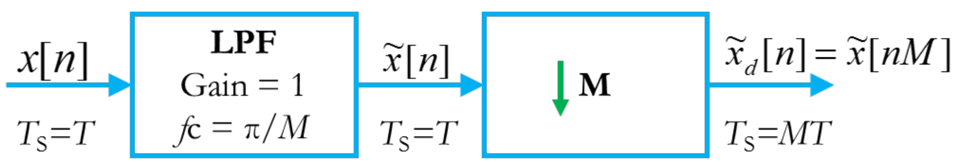
- *Signal Interpolation* is an upsampling and filtering technique applies on a discrete-time signal, aims at increasing the number of samples by factor L through inserting L-1 zeros in-between samples, multiplying the amplitude by L, and smoothing interpolated signal.



$$x_i[n] = \begin{cases} x[n/L] = x\left(\frac{nT}{L}\right), & n = \{0, \pm L, \pm 2L, \dots\} \\ 0, & otherwise \end{cases}$$

Representation of upsampling system by an integer factor L

- *Signal Decimation*—a complementary process for interpolation—is a filtering and downsampling technique applies on a discrete-time signal, aims at decreasing the number of samples by factor M through resampling the signal every M^{th} samples and discarding the rest samples. LPF is a low pass filter used to eliminate aliasing.



$$\tilde{x}_d[n] = x[nM] = x_c(nMT)$$

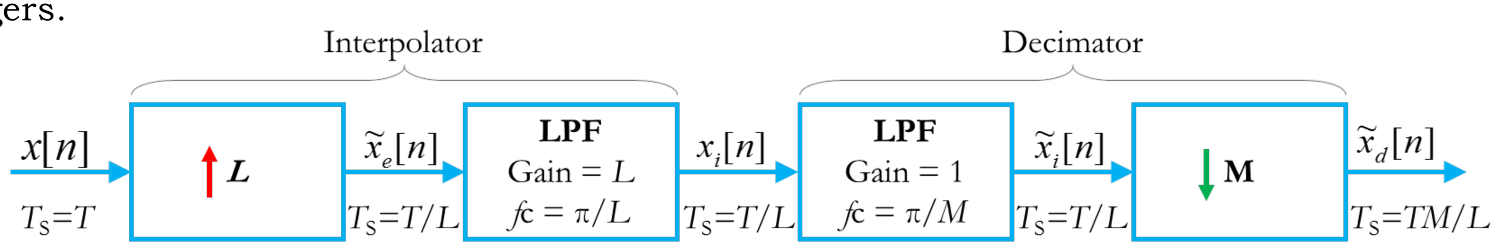
Representation of downsampling system by integer factor M

Data Analysis – Normalization

- If all vehicle signatures have to be normalized such that signature length = 200 samples, a resampling at non-integer factor is needed.

- It is possible to change the sampling rate by a non-integer factor by combining both decimation and interpolation processes, such that the interpolator increases its sampling rate by a factor L, followed by a linear time-invariant LPF to eliminate signal images, and a decimator in the final stage which decreases its sampling rate by a factor M.

- The generated signal will have an effective sampling period of $T_S = TM/L$, where both factors L and M are integers.



Representation of combined upsampling and downsampling systems

- The length distribution of vehicle signatures in the dataset was analyzed. The normalized length was set equal to the mean of length distribution.

Data Analysis – Correlation

- The objective of this analysis is to evaluate the difference/similarity in vehicle magnetic signature between vehicles of the same class, as well as with vehicles of different classes.
- Cross-correlation method was used to measure the similarity of two waveforms as a function of a time-lag applied to one of them.
- Correlation between signals can be either linear (e.g., impulses signal) or circular (e.g., periodic).
- A correlation coefficient is used to express the correlation strength between signals.
- The Pearson correlation coefficient is the most common measure of linear dependence between two quantities.
- The correlation coefficient for two random variables, A and B, is defined as follows

$$\rho(A,B) = \frac{cov(A,B)}{\sigma_A \sigma_B} = \frac{1}{N-1} \sum_{i=1}^{N} \frac{(A_i - \mu_A)(B_i - \mu_B)}{\sigma_A \sigma_B}$$

- where μ_A and σ_A are the mean and STD of A, and μ_B and σ_B are the mean and STD of B, respectively

Data Analysis – Correlation

- Since we had multiple signatures, the correlation coefficient matrix for all signals is found by combining the correlation coefficients for each pairwise signatures $\rho(S_A, S_B)$ as follows

$$R = \begin{bmatrix} \rho(S_1,S_1) & \rho(S_1,S_2) & \rho(S_1,S_3) & \rho(S_1,S_4) & \cdots & \rho(S_1,S_m) \\ \rho(S_2,S_1) & \rho(S_2,S_2) & \rho(S_2,S_3) & \rho(S_2,S_4) & \cdots & \rho(S_2,S_m) \\ \rho(S_3,S_1) & \rho(S_3,S_2) & \rho(S_3,S_3) & \rho(S_3,S_4) & \cdots & \rho(S_3,S_m) \\ \rho(S_4,S_1) & \rho(S_4,S_2) & \rho(S_4,S_3) & \rho(S_4,S_4) & \cdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho(S_m,S_1) & \cdots & \cdots & \cdots & \cdots & \rho(S_m,S_m) \end{bmatrix}$$

- The diagonal entries are always equal to 1 as all signals are directly correlated to themselves.

- The p-values matrix was also found for all pairwise combination. A small p-values would reject the null hypothesis and identifying significant correlations.

Data Analysis

Figures Labeling

CxxVSS

Class
{1—13}

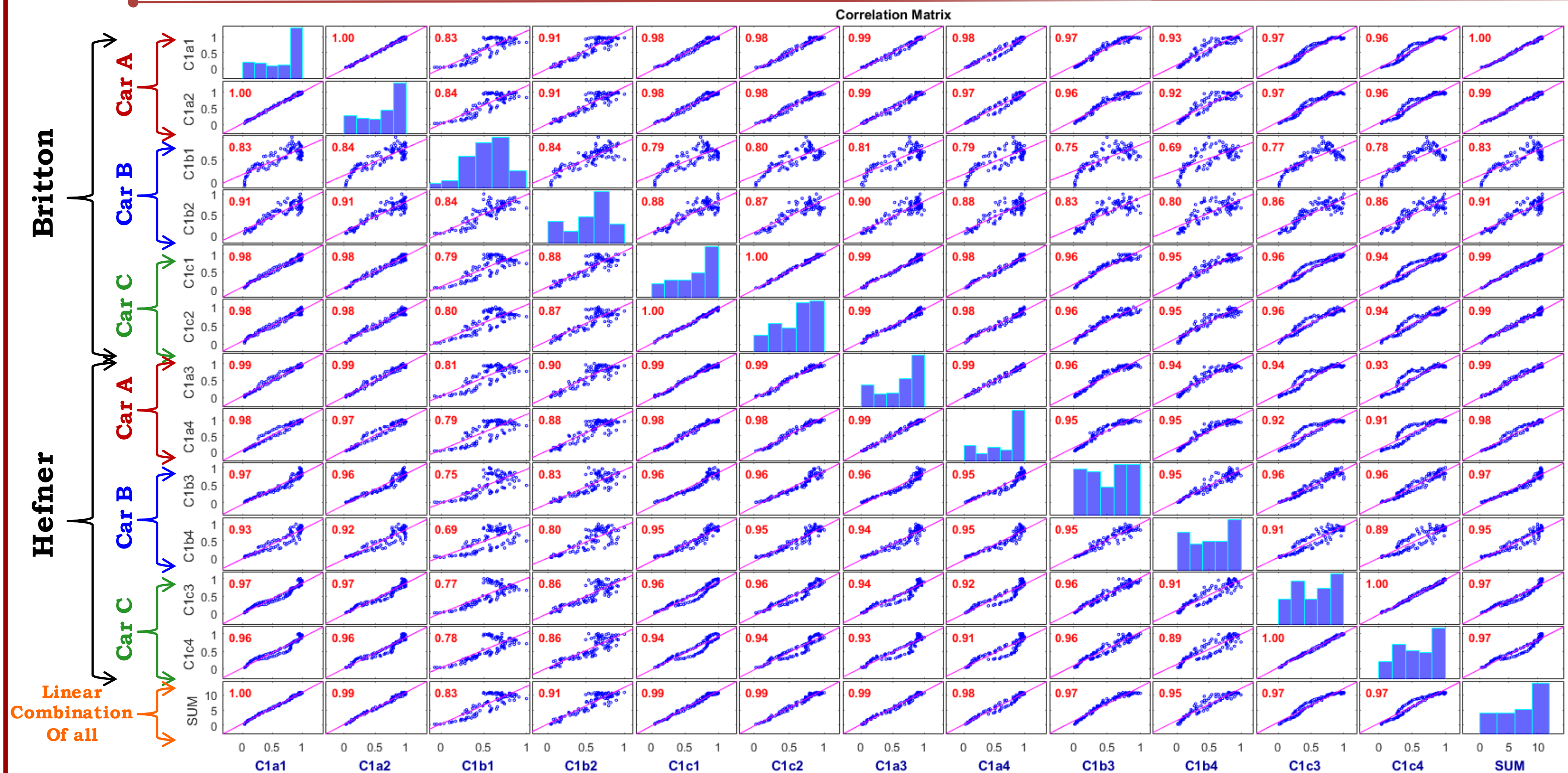
Vehicle
{a—z}

Site
{Britton 1—2}
{Hefner 3—4}

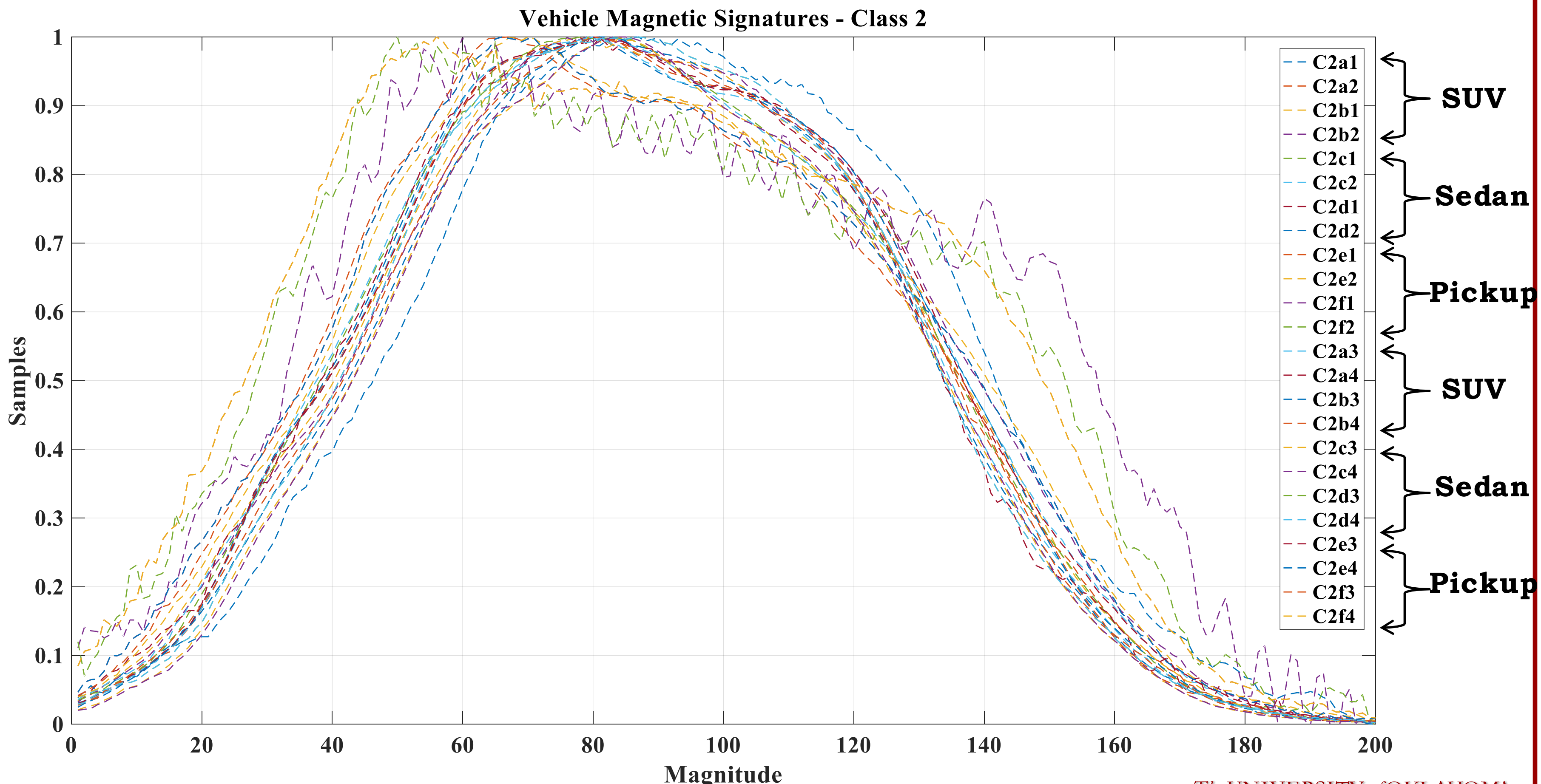
Ex: **C12a1**
Class 12 | vehicle a | IDL1 at Britton

Data Analysis – Class 1

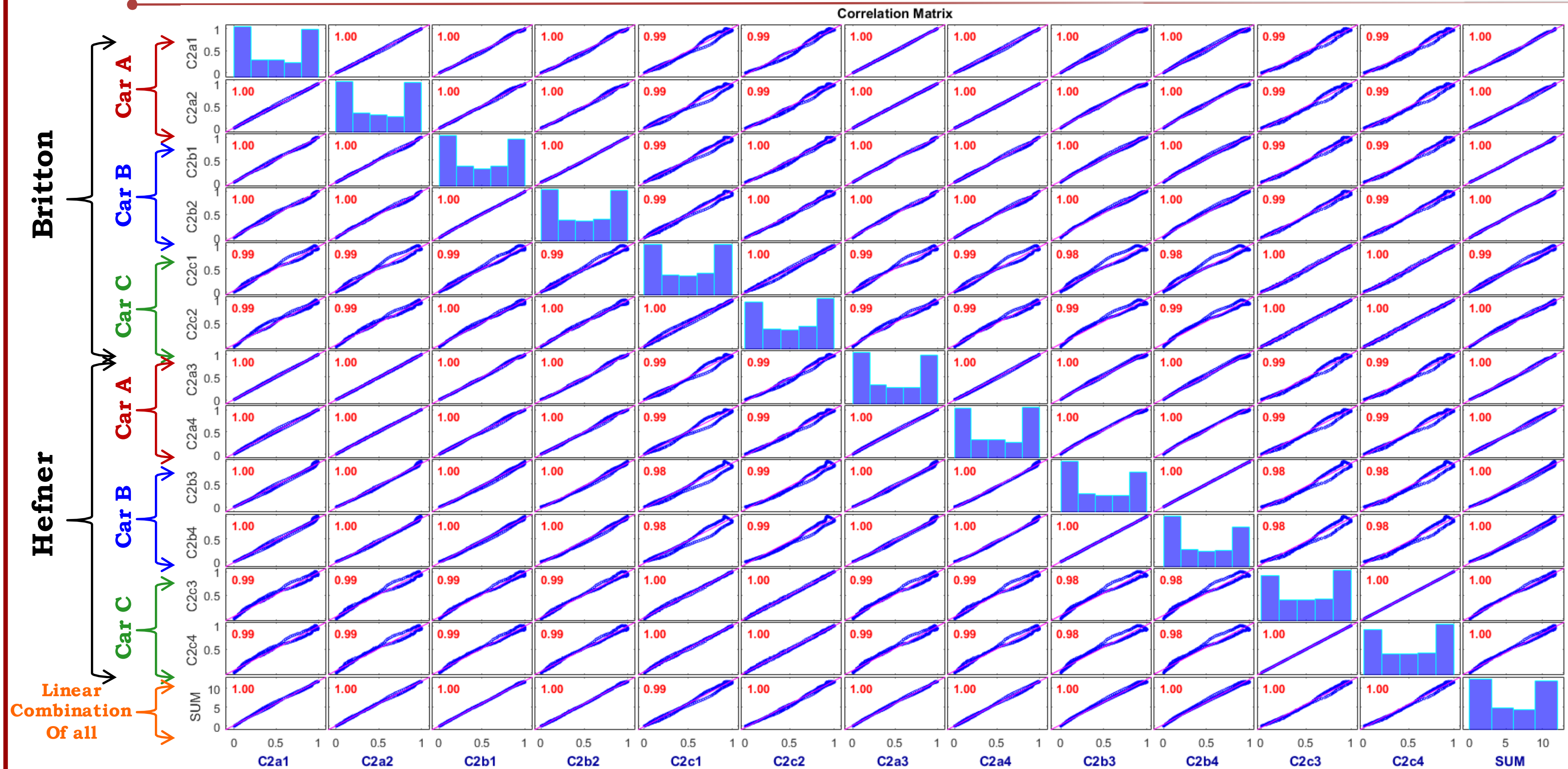
Data Analysis – Class 1



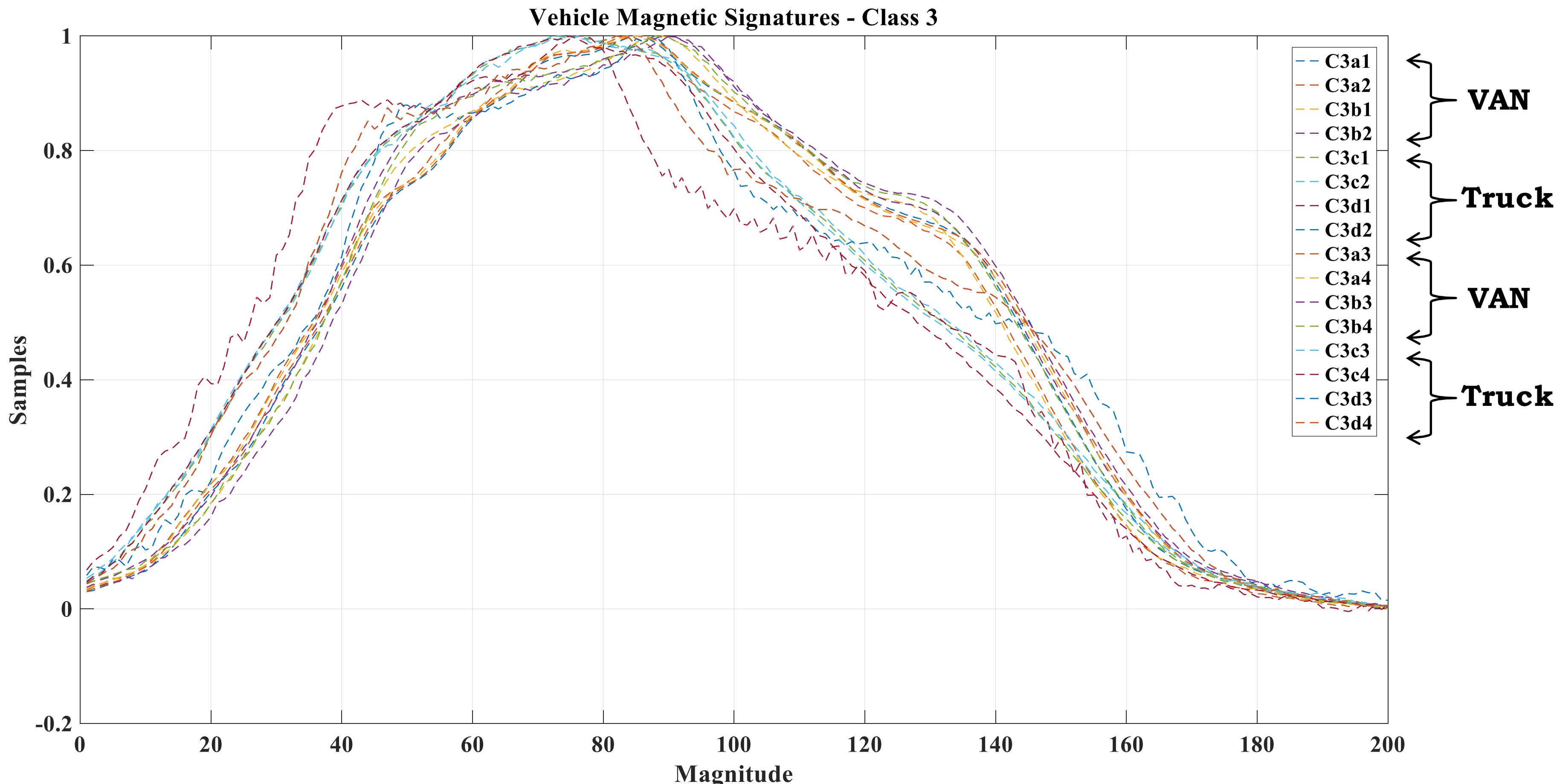
Data Analysis – Class 2



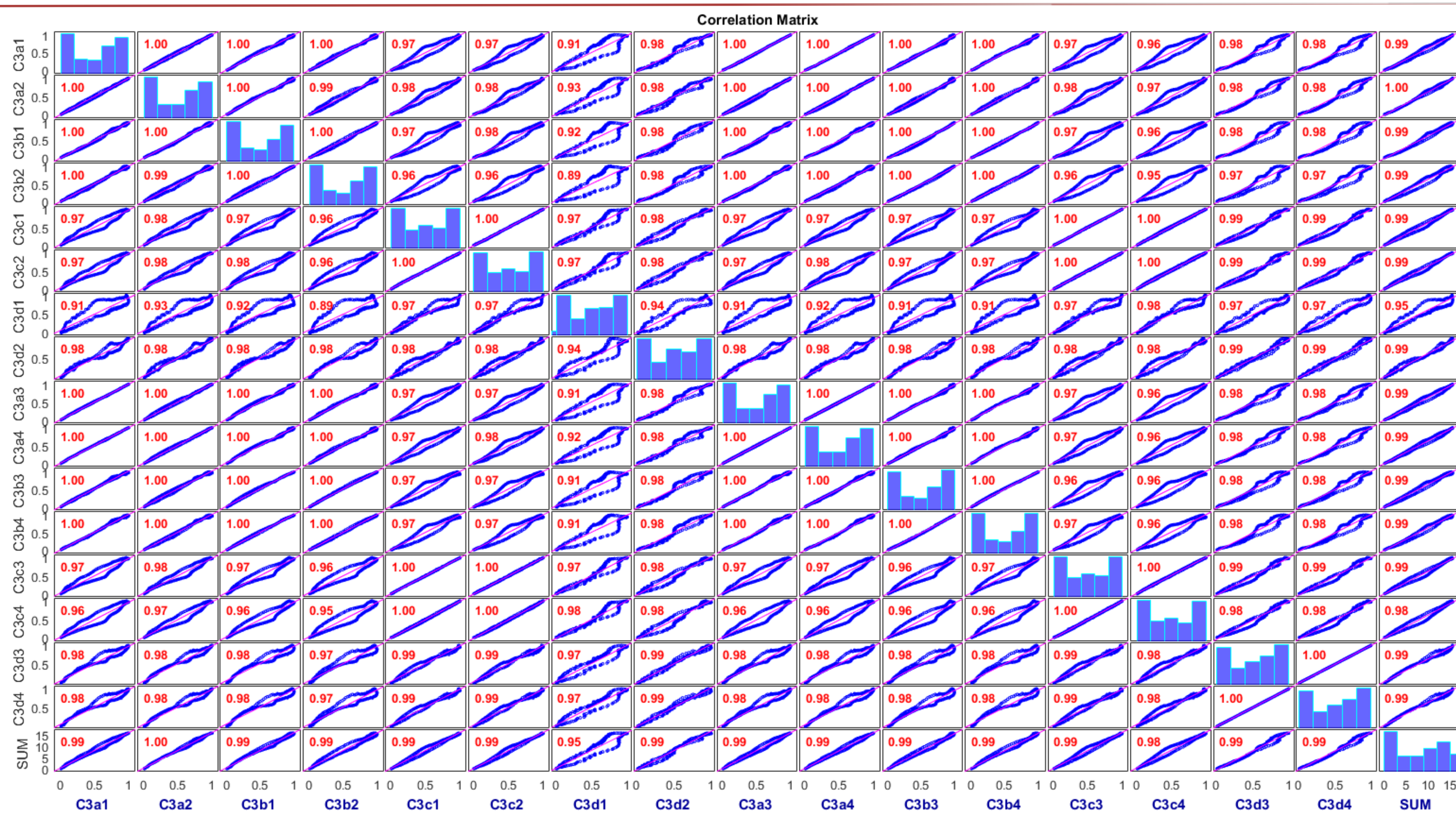
Data Analysis – Class 2



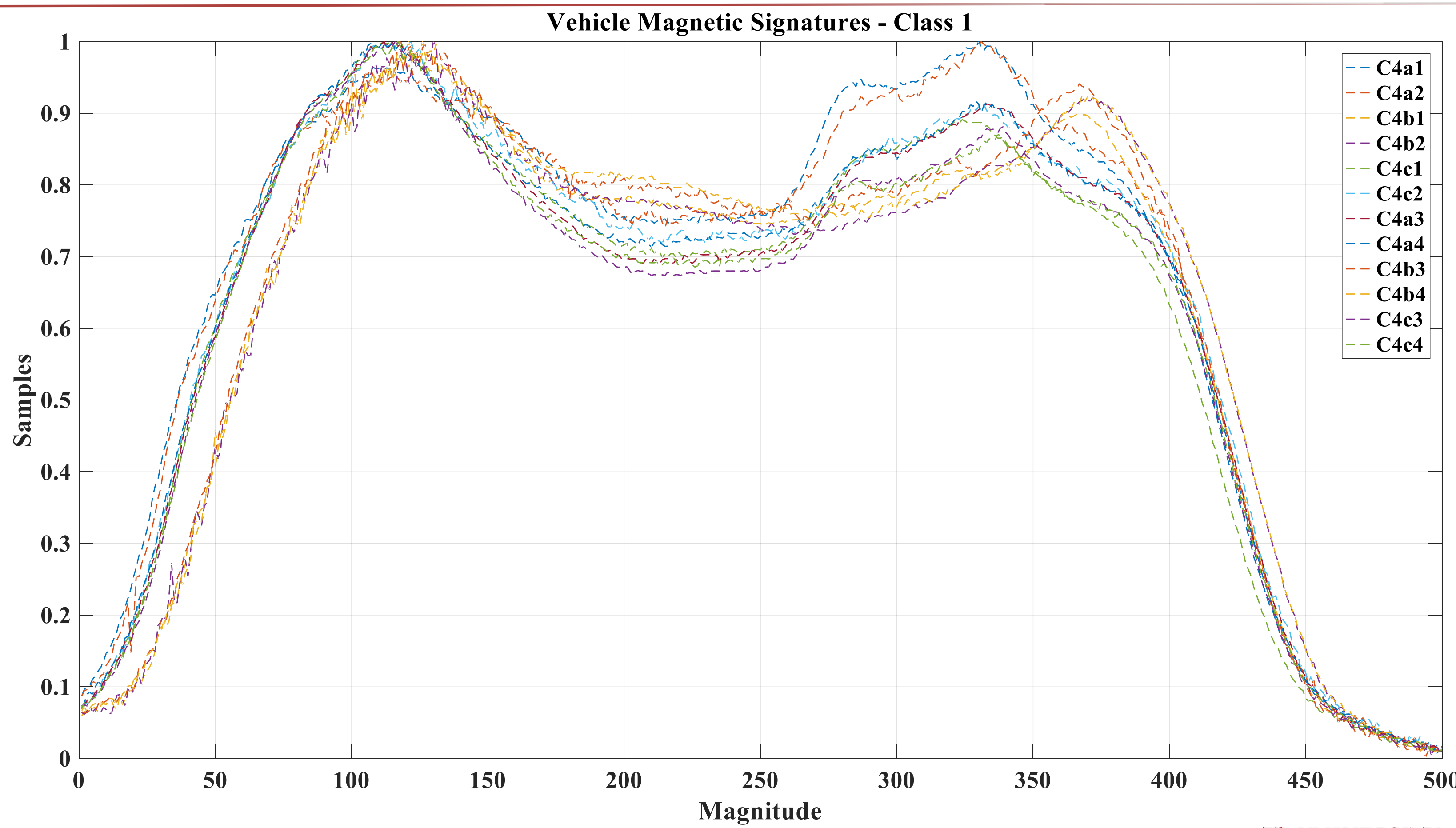
Data Analysis – Class 3



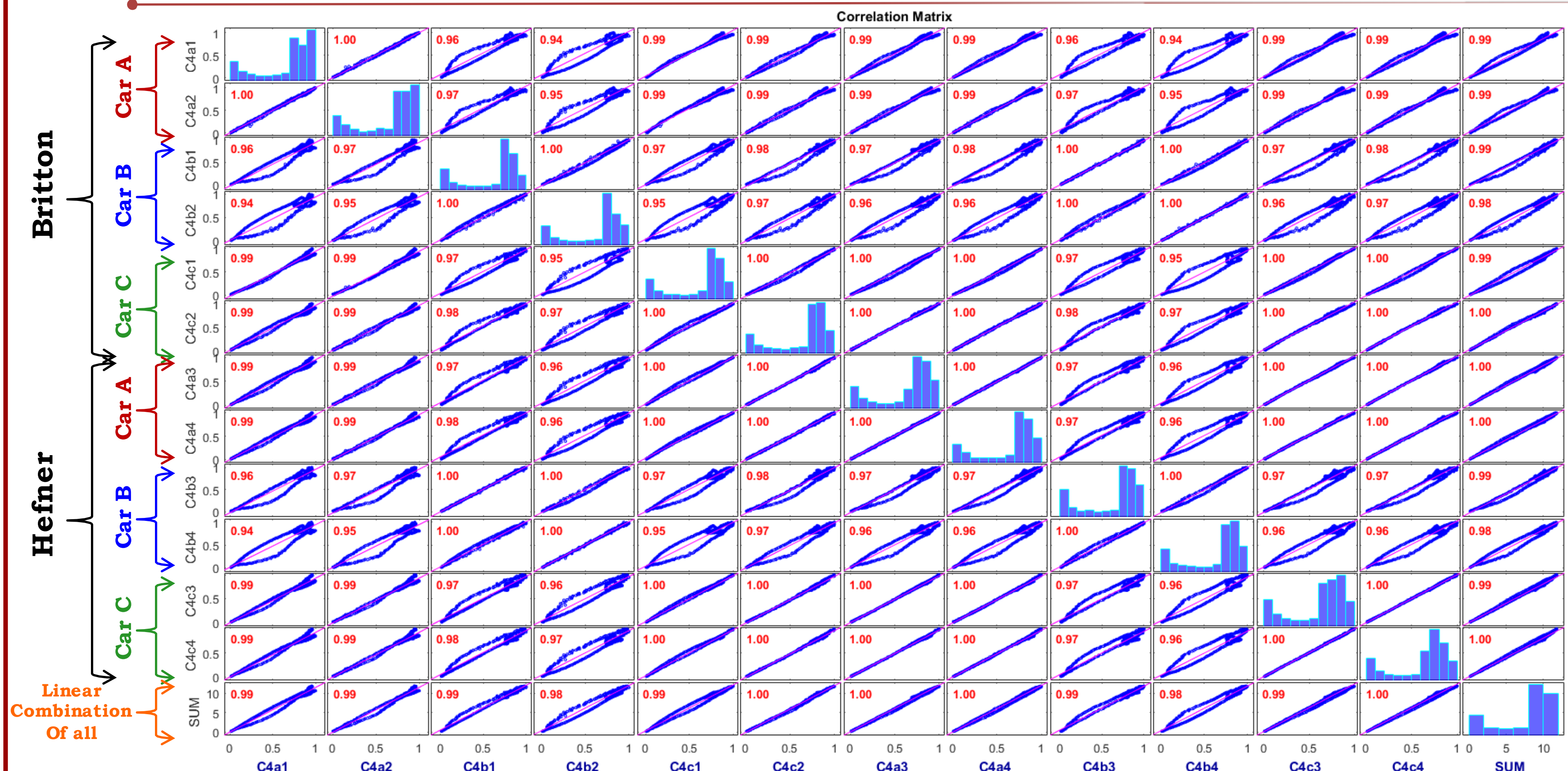
Data Analysis – Class 3



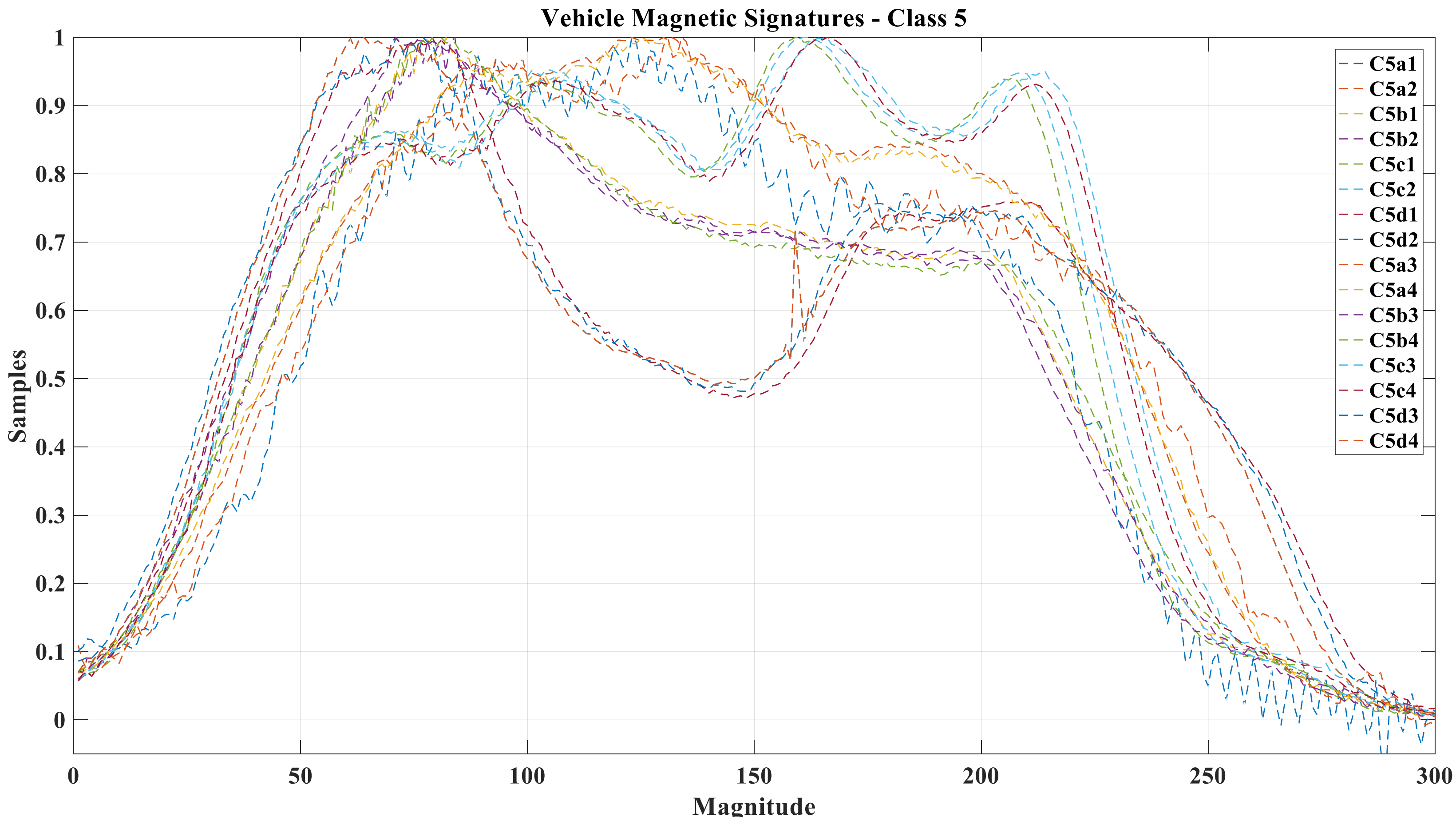
Data Analysis – Class 4



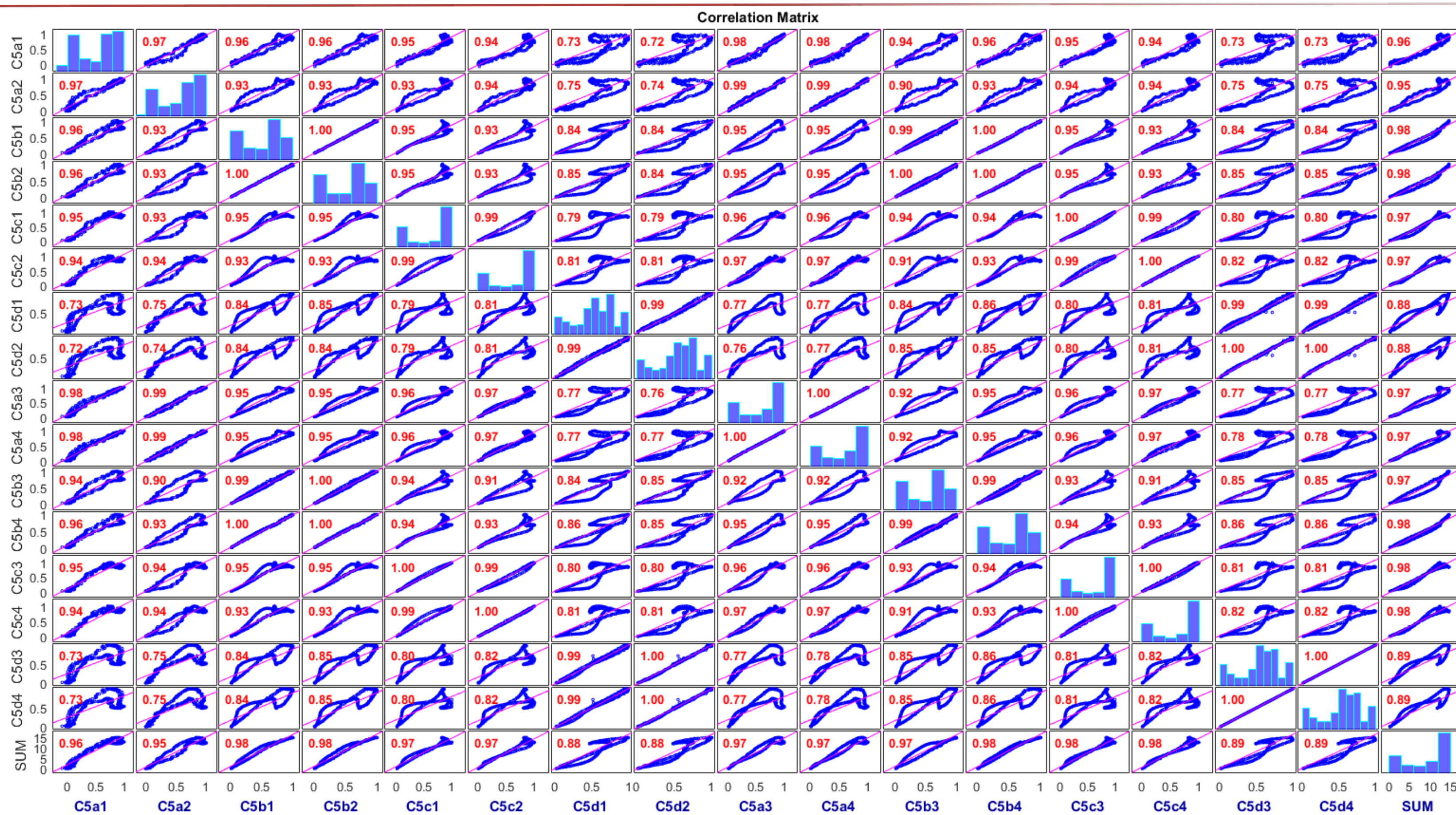
Data Analysis – Class 4



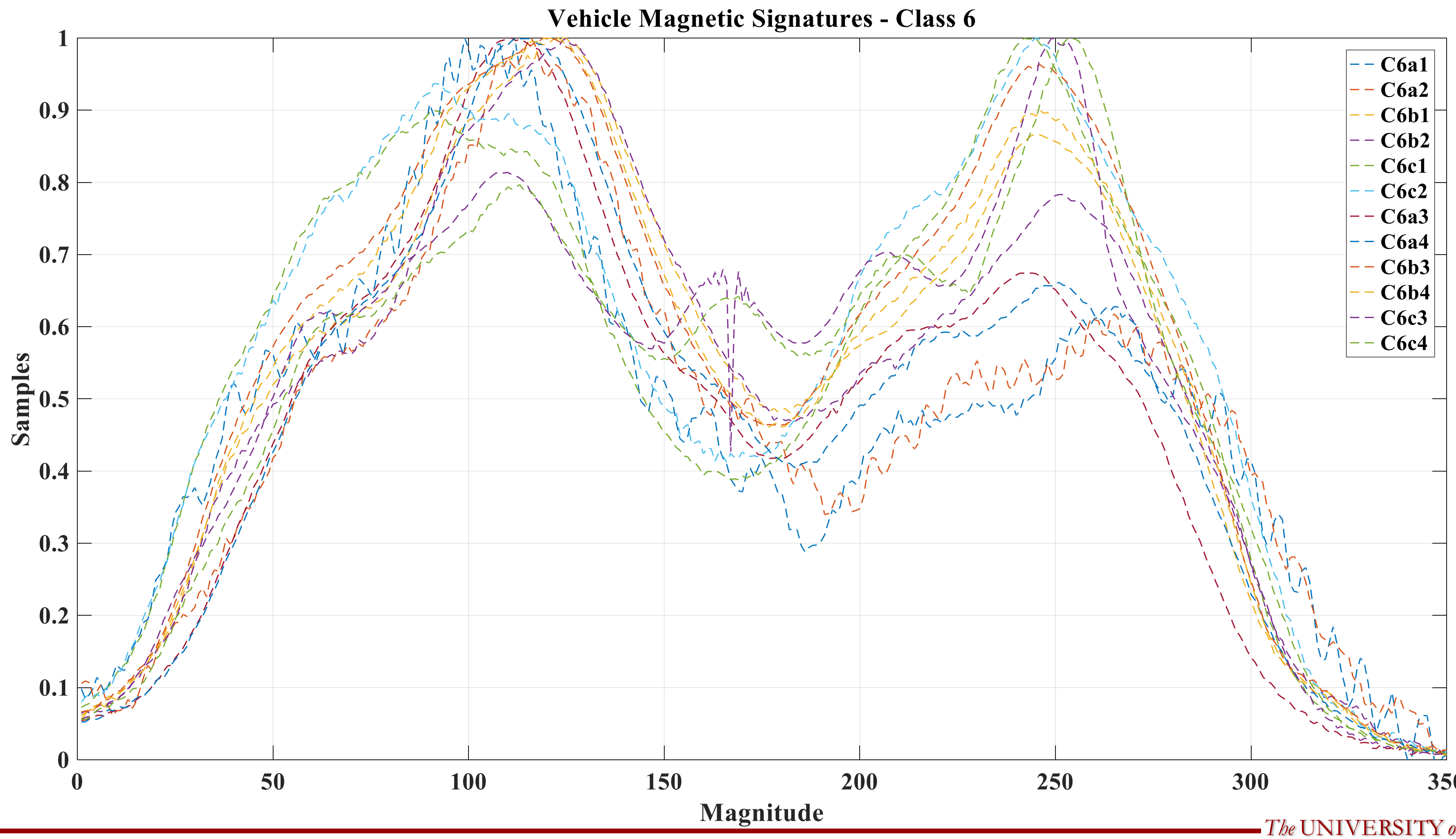
Data Analysis – Class 5



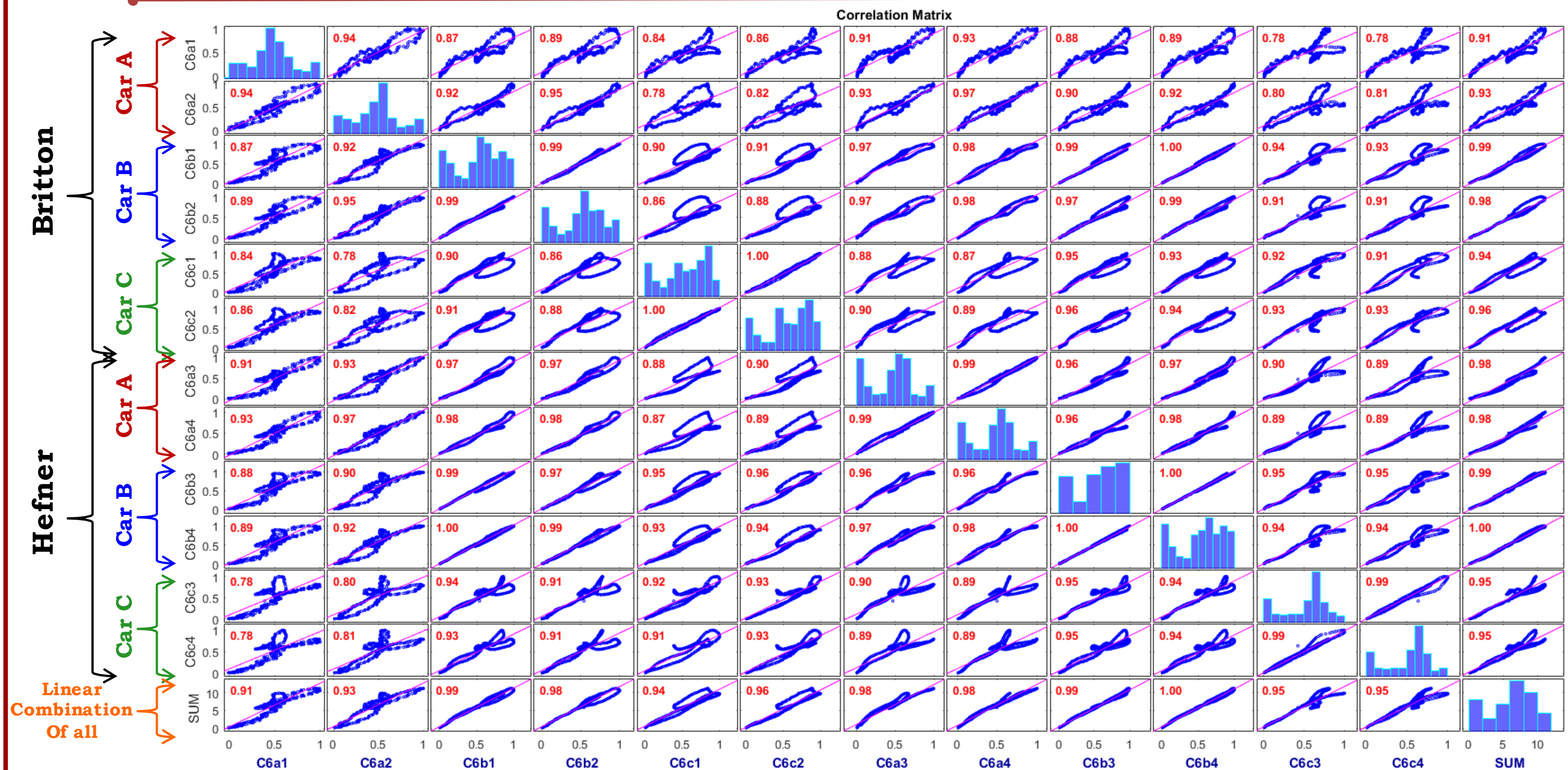
Data Analysis – Class 5



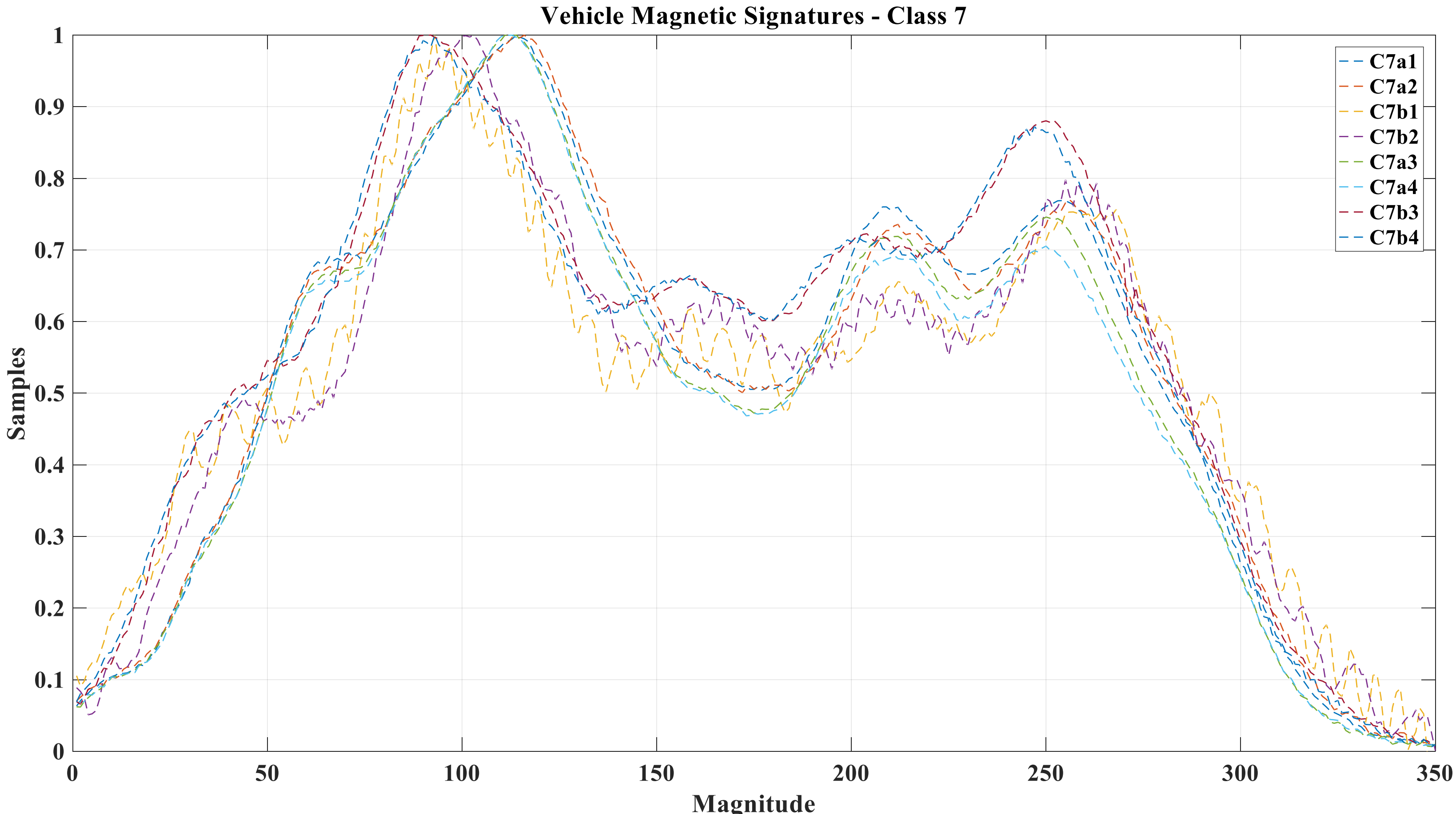
Data Analysis – Class 6



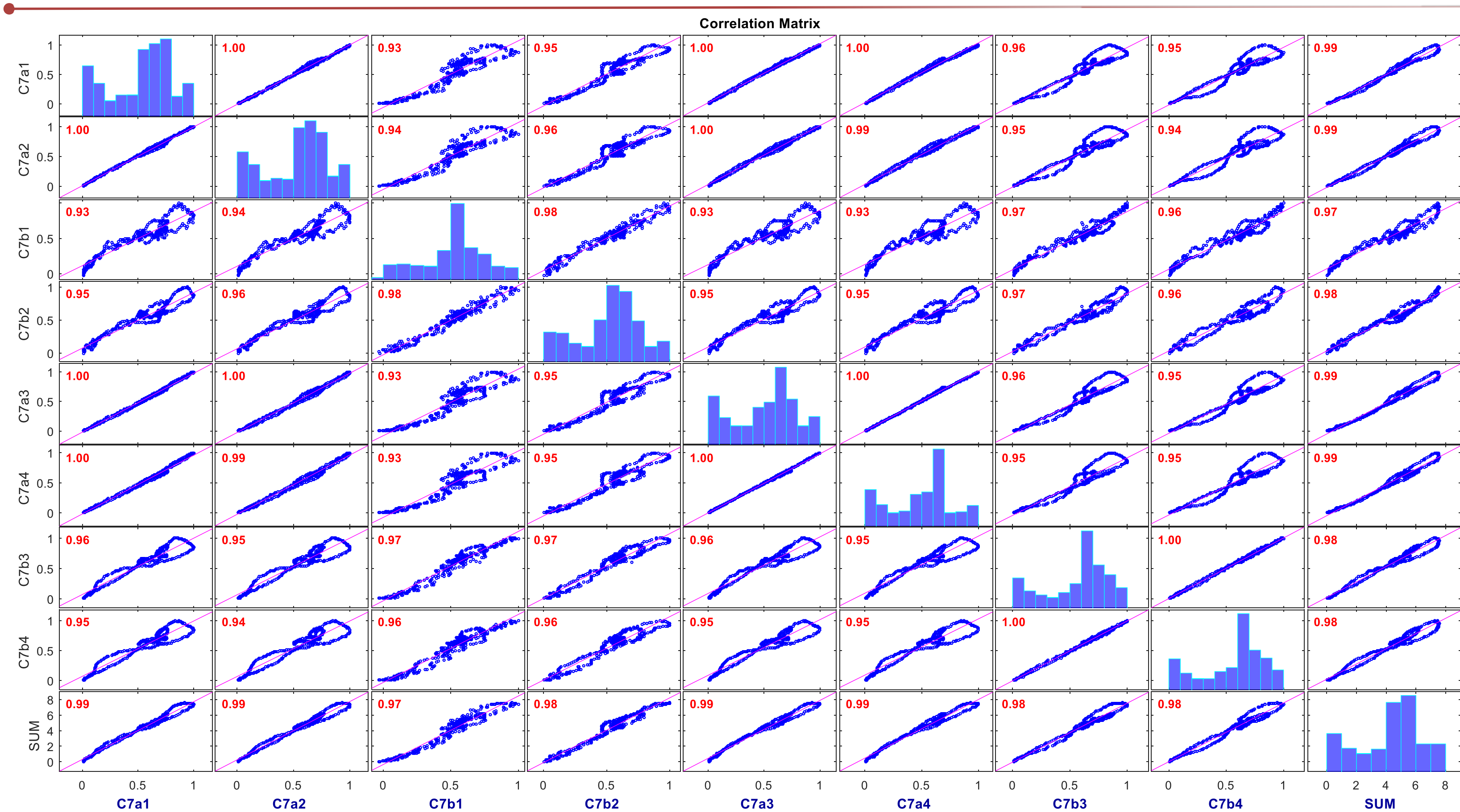
Data Analysis – Class 6



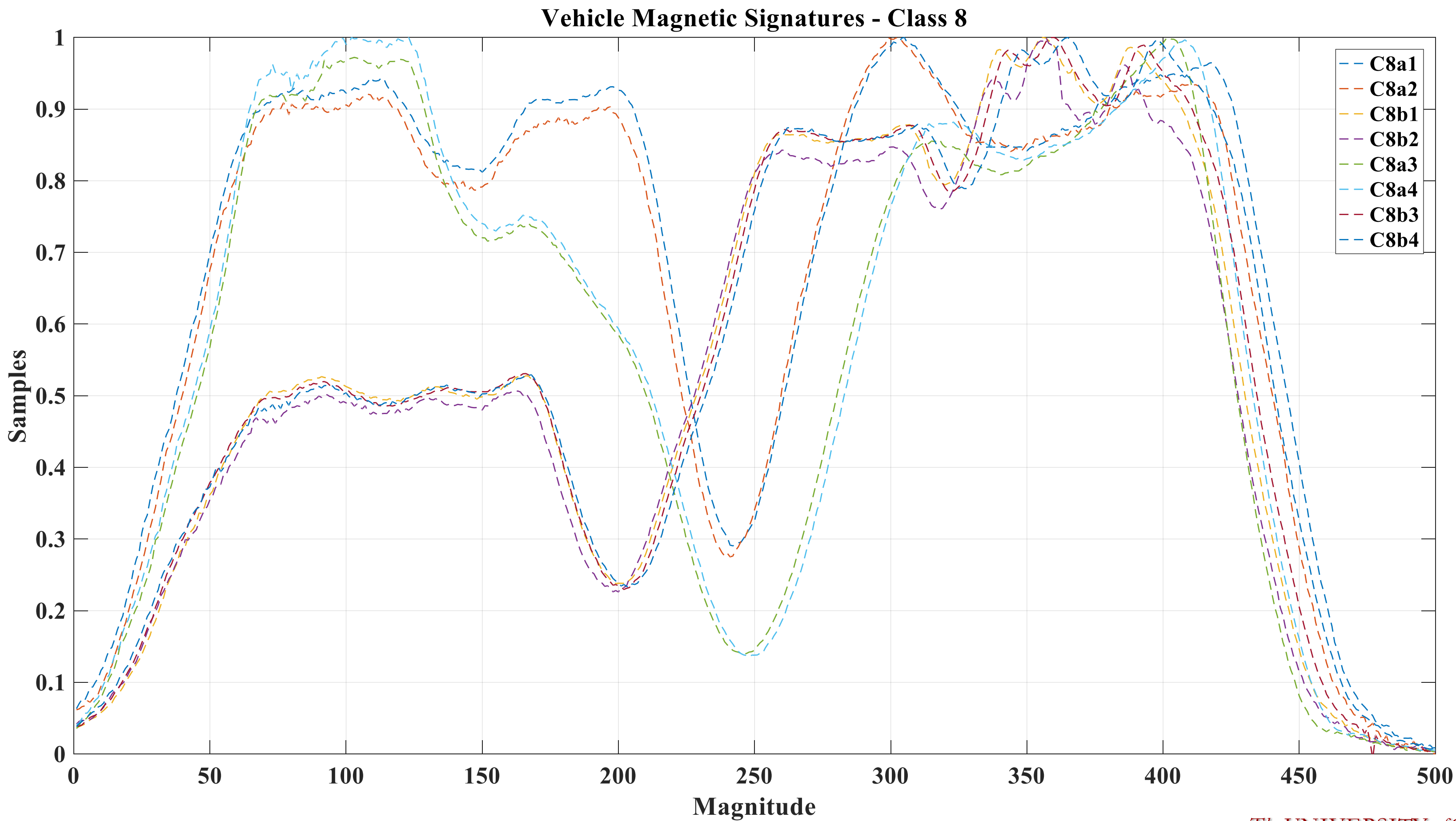
Data Analysis – Class 7



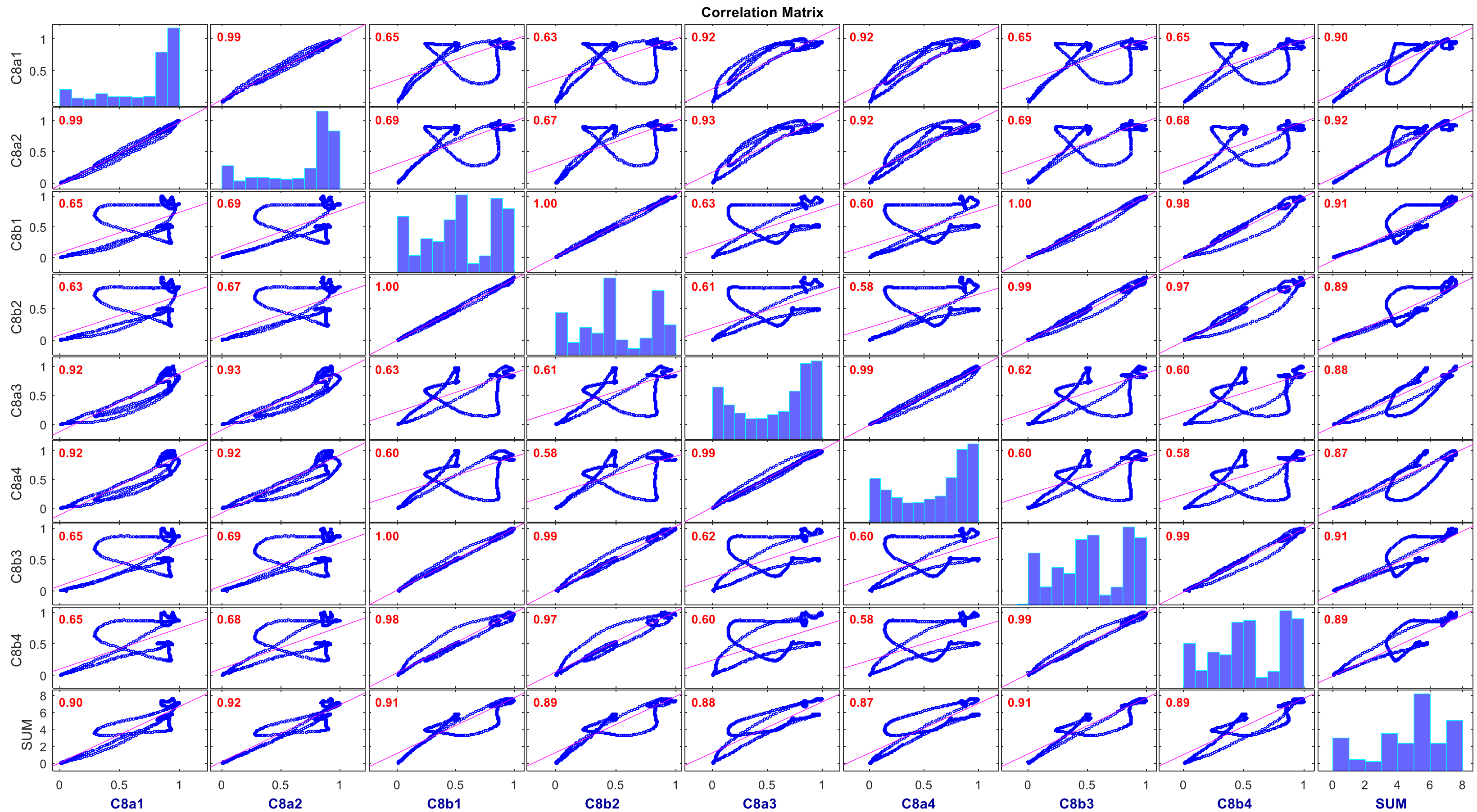
Data Analysis – Class 7



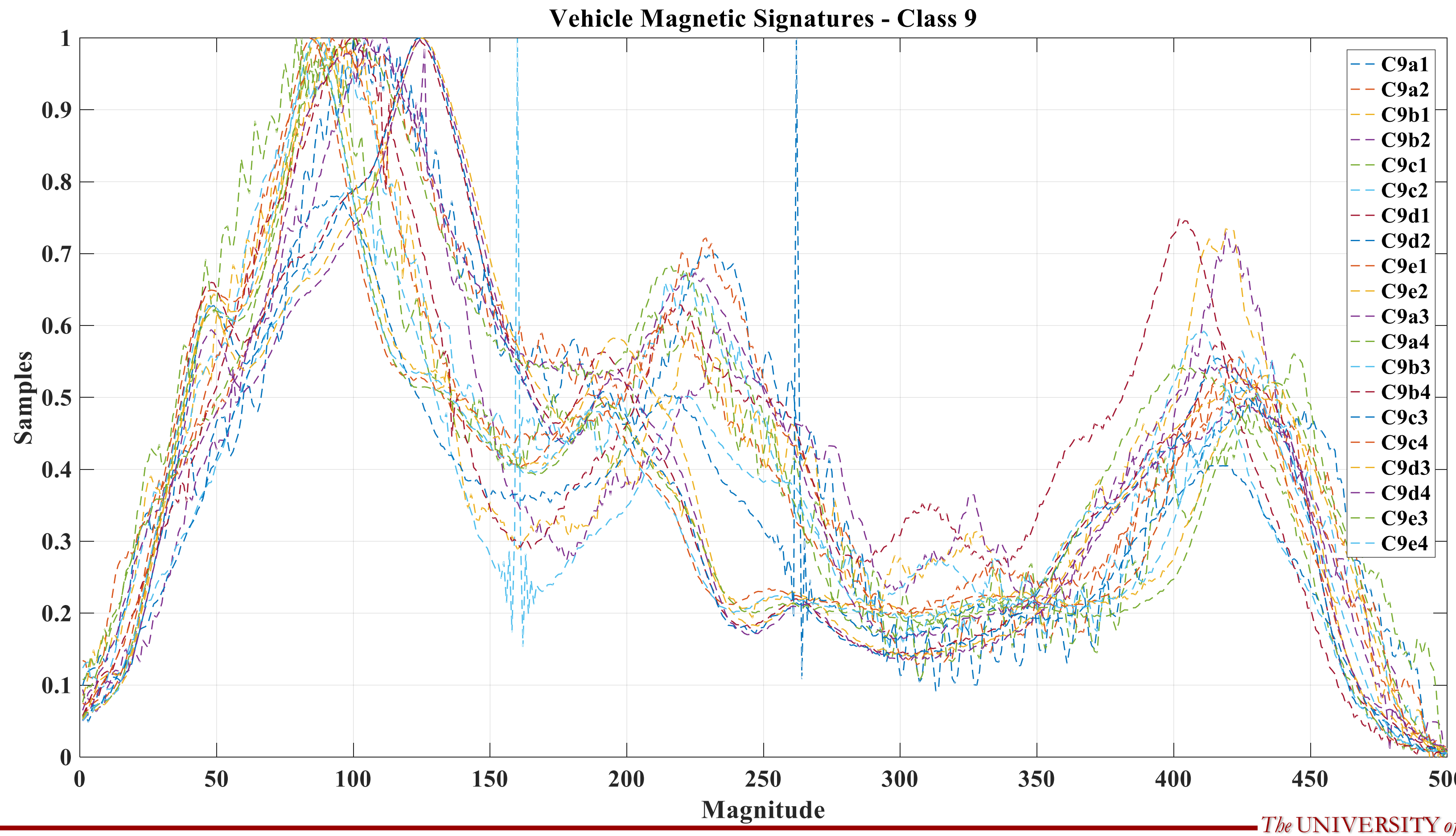
Data Analysis – Class 8



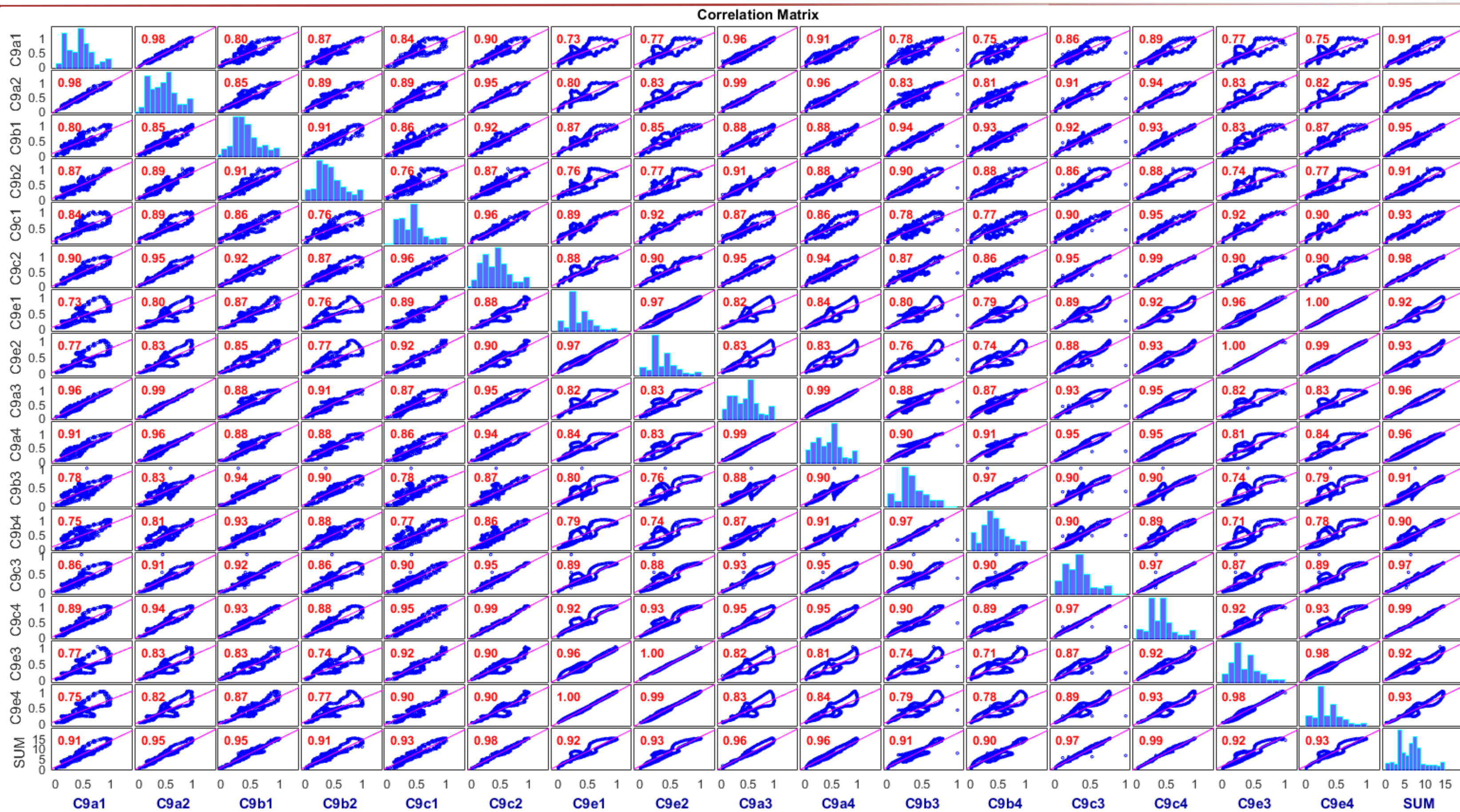
Data Analysis – Class 8



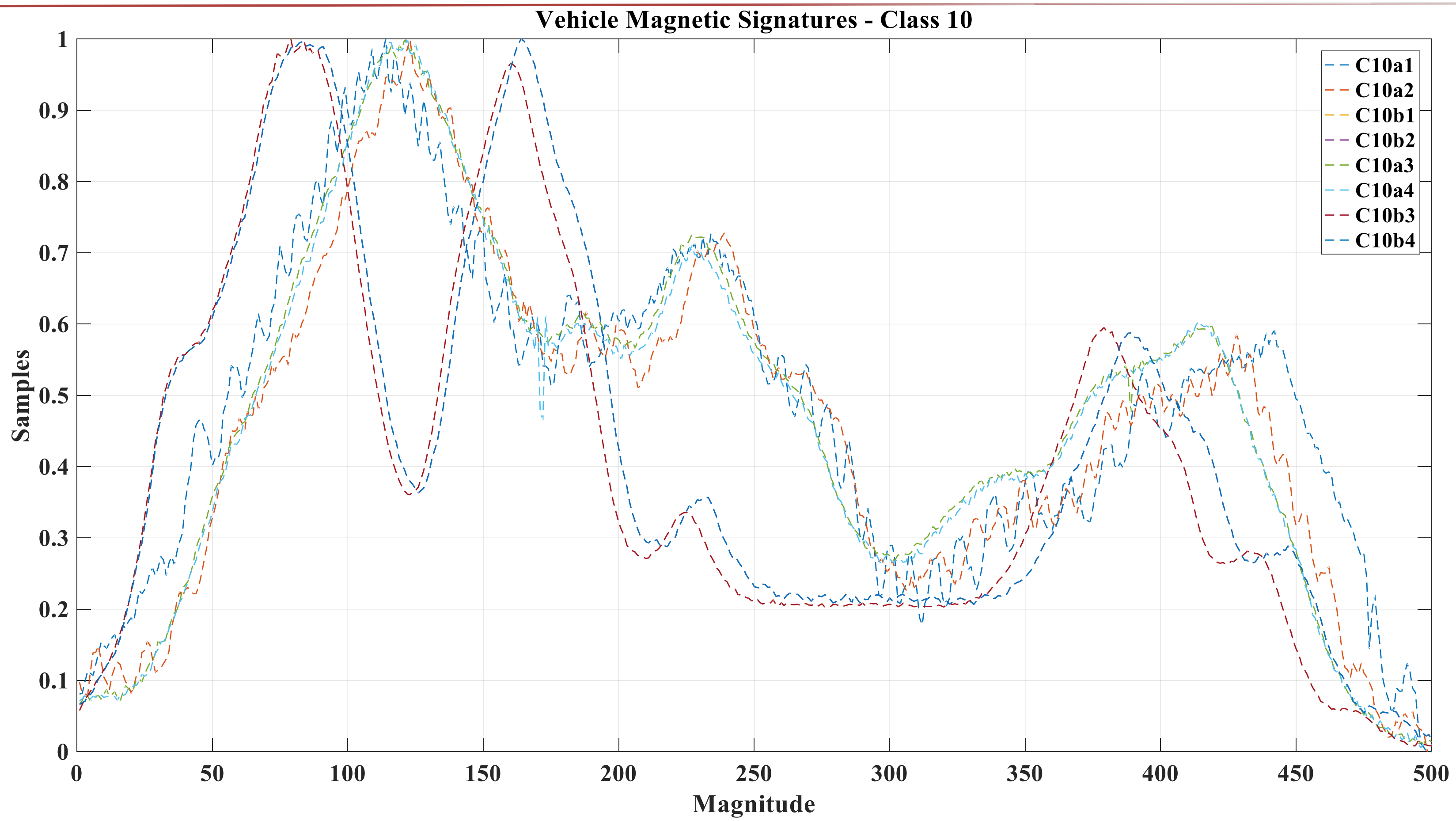
Data Analysis – Class 9



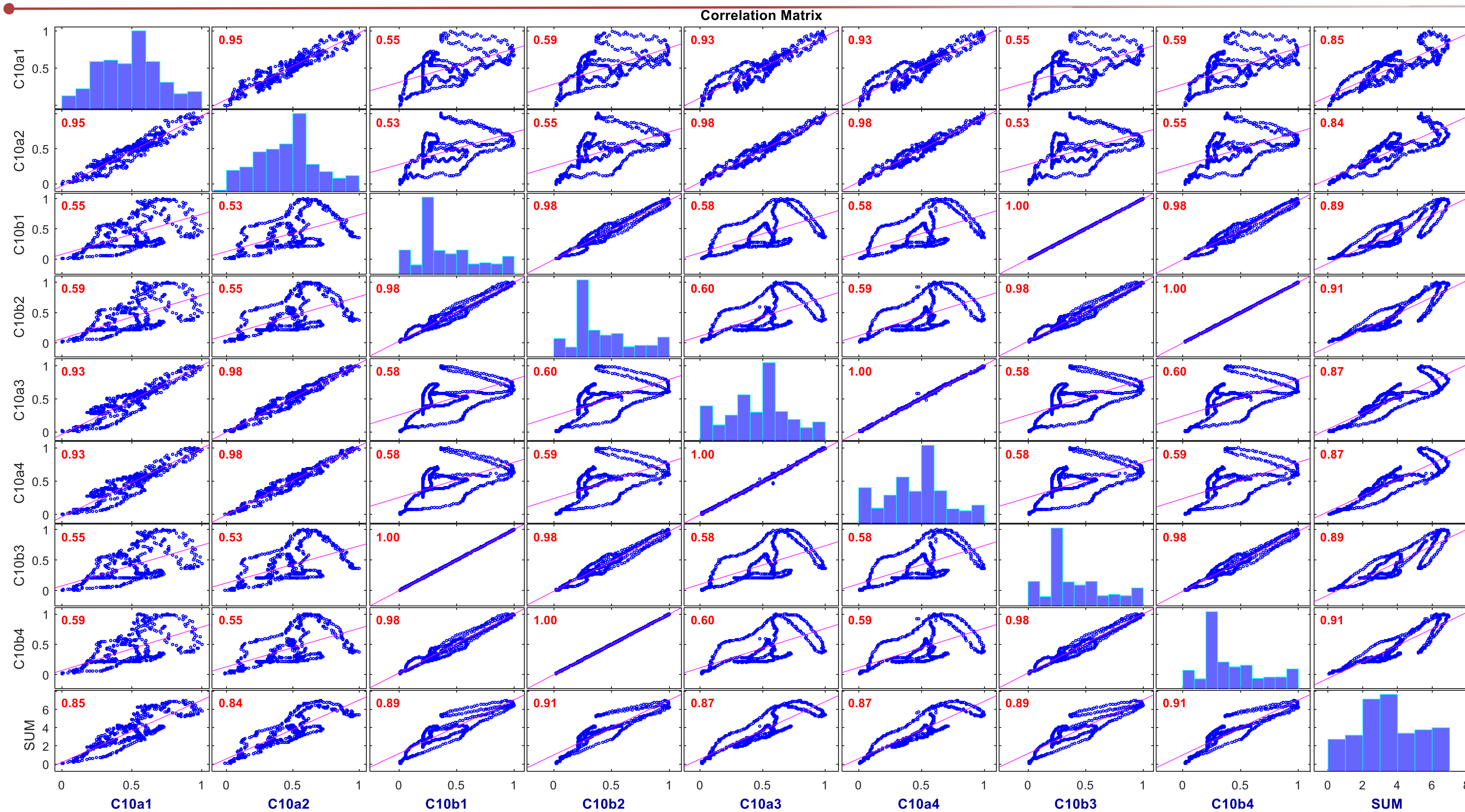
Data Analysis – Class 9



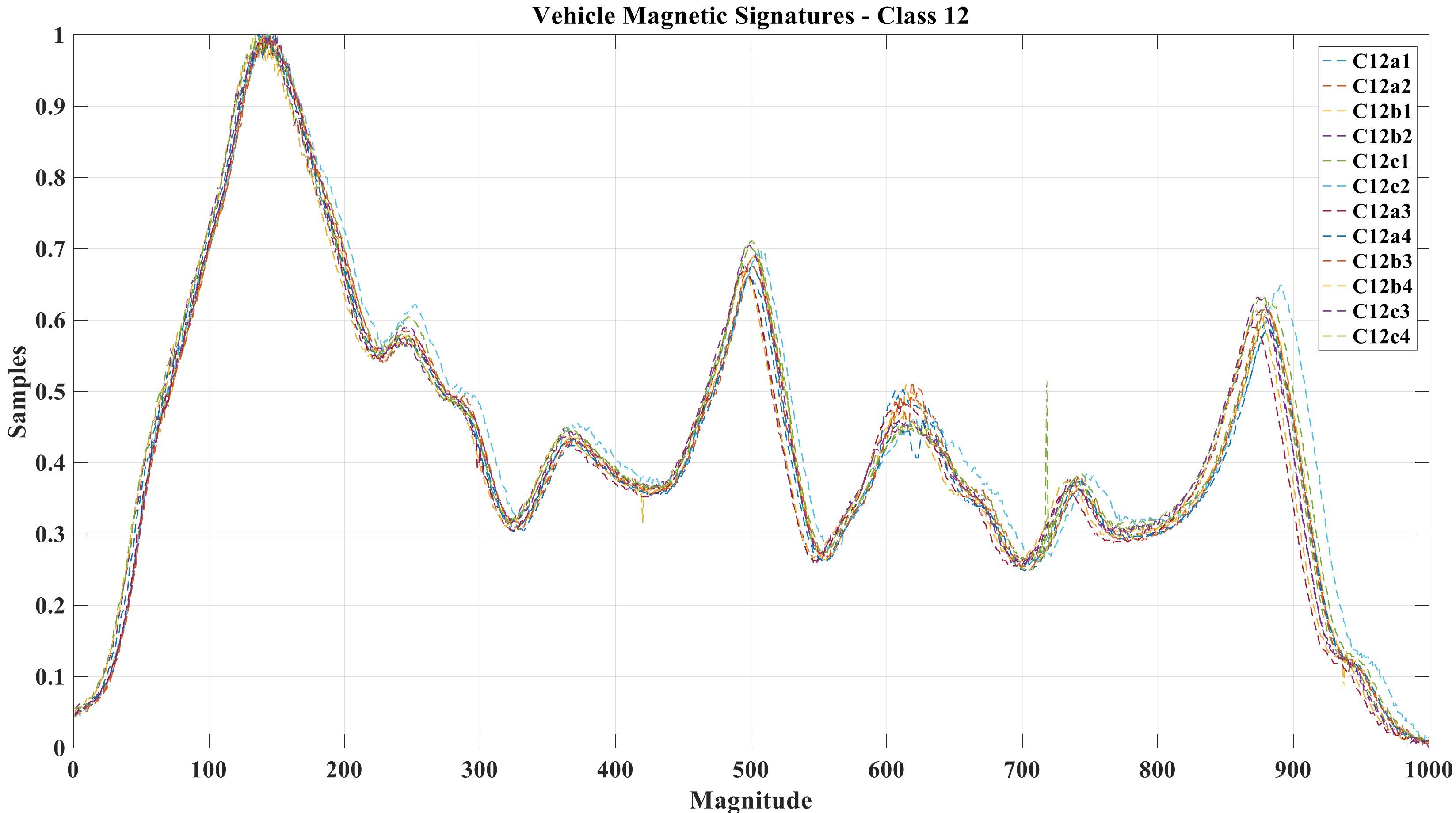
Data Analysis – Class 10



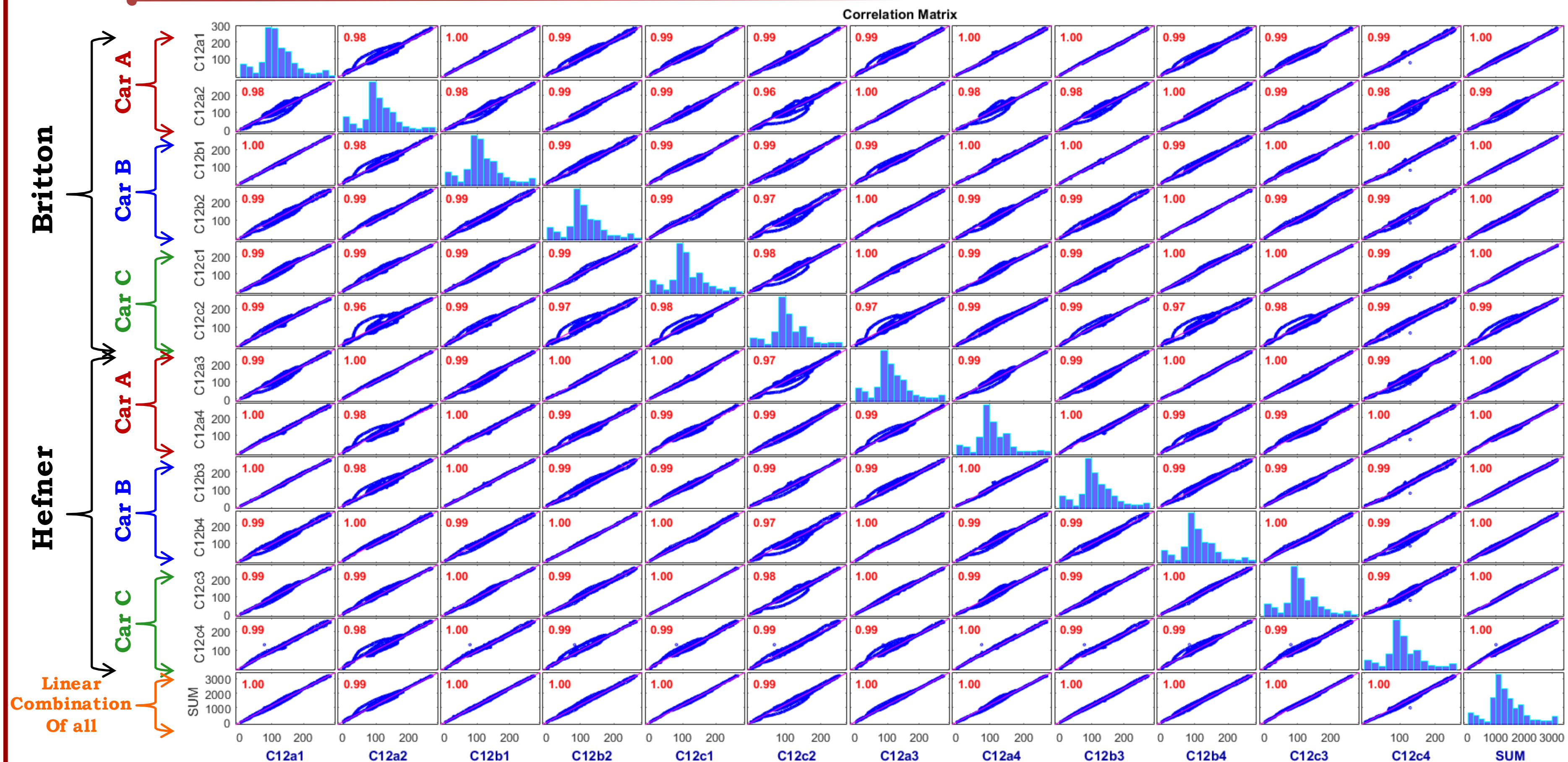
Data Analysis – Class 10



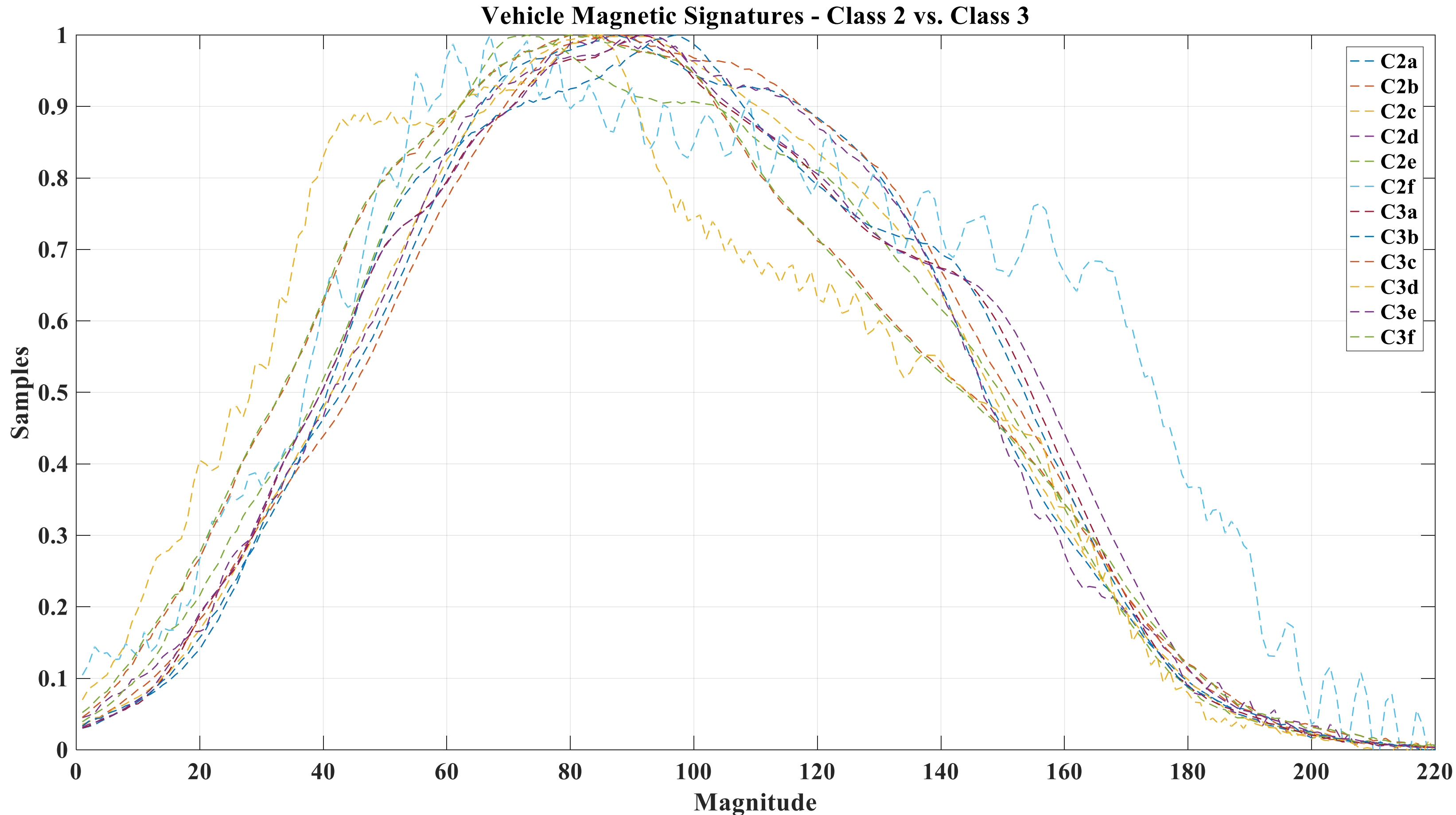
Data Analysis – Class 12



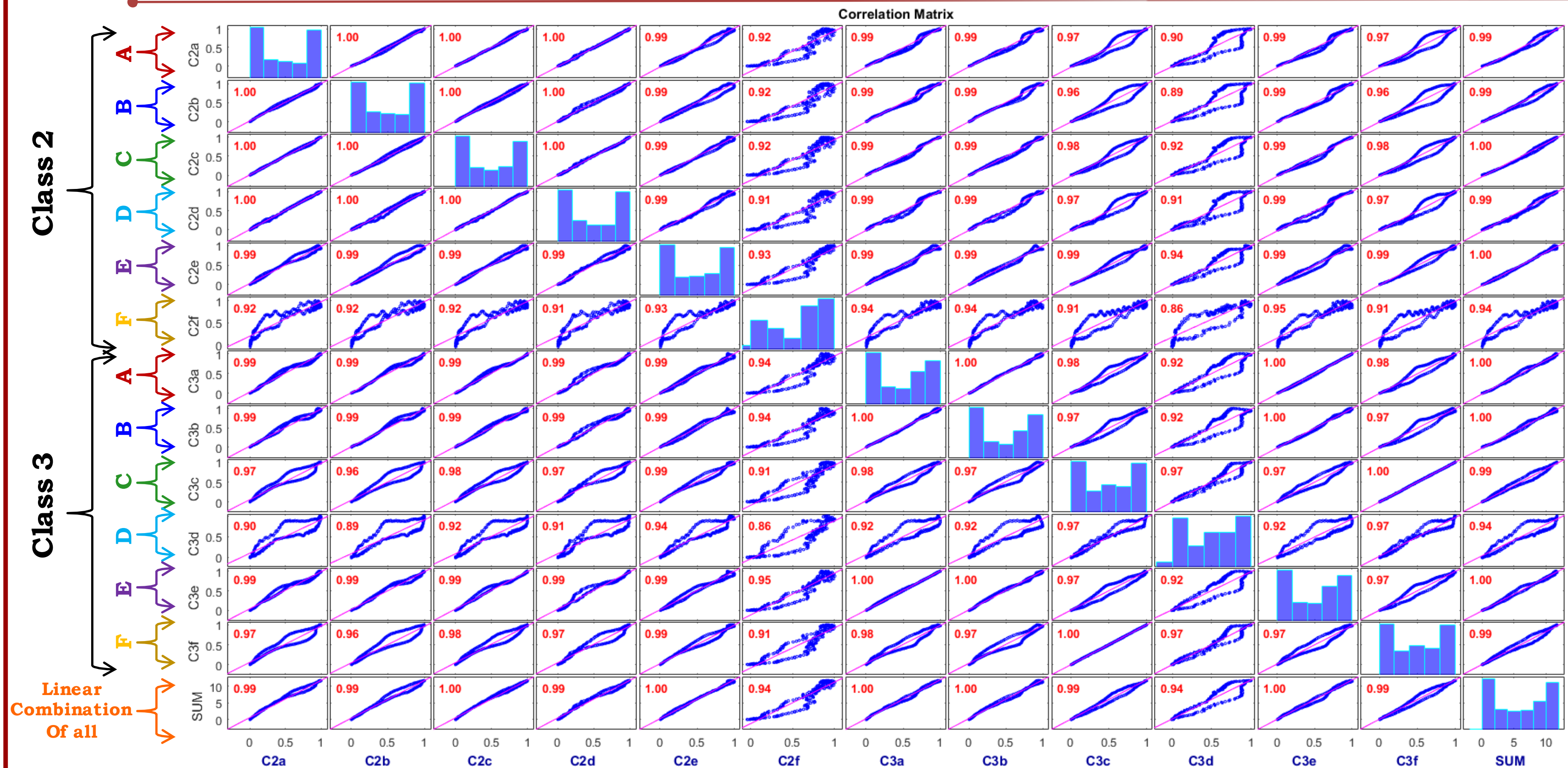
Data Analysis – Class 12



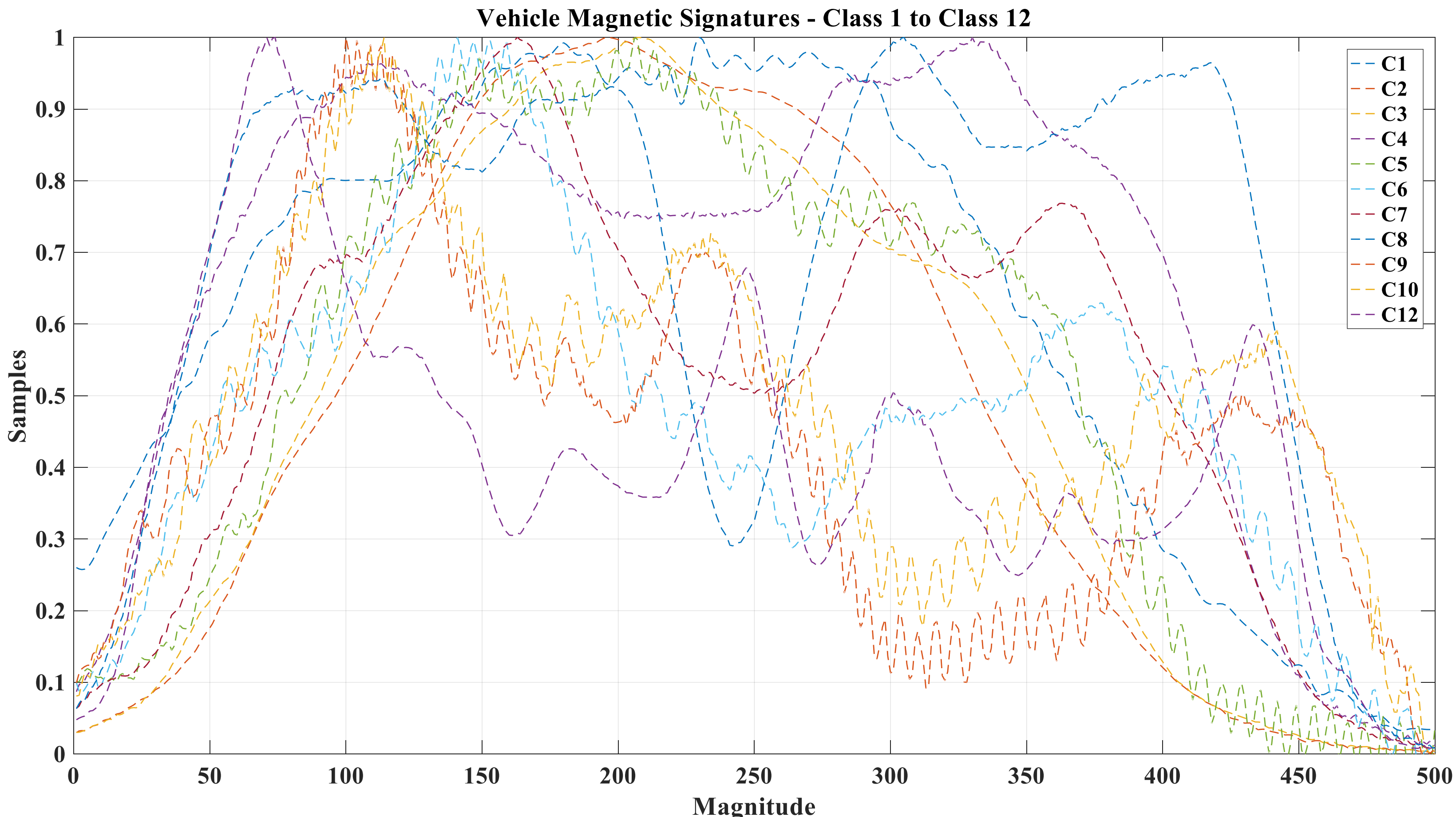
Data Analysis – Class 2 vs. Class 3



Data Analysis – Class 2 vs. Class 3



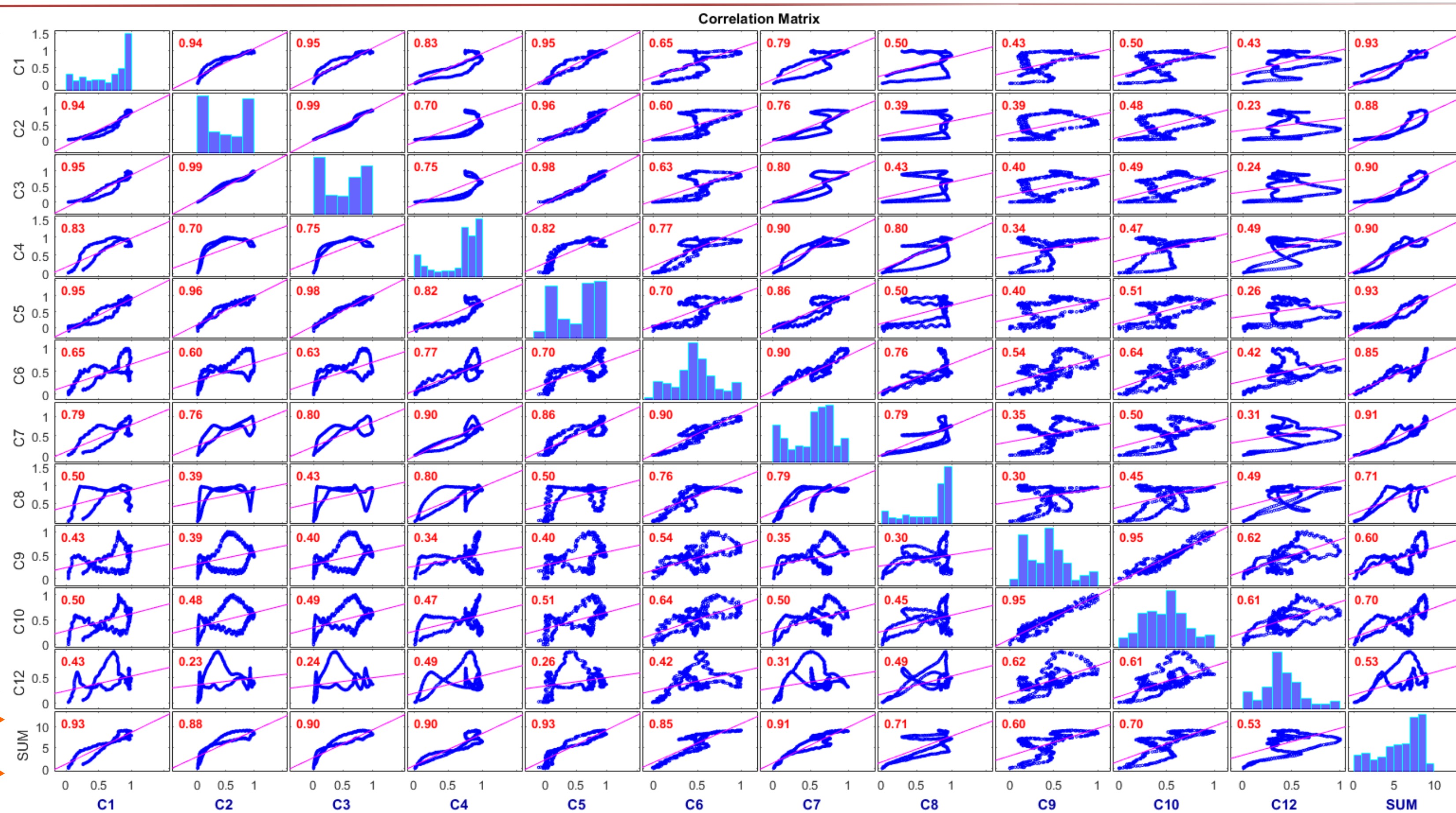
Data Analysis – ALL vs. ALL



Data Analysis – ALL vs. ALL

FHWA Class 1—12

Linear Combination Of all



Conclusion

- Inductive loops can generate highly correlated magnetic signature for same vehicle at multiple sites as long as the vehicle has the same composition of ferrous materials in its structure over all sites.
- A high correlation factor in magnetic signatures for vehicles of the same class can be observed in Class 1, 2, 3, 4, 6, 7, and 12.
- The correlation factor is less significant for Class 5 and 9 as they have significant variation in their vehicles structure.
- Signatures for vehicles of Class 8 showed insignificant correlation; same for Class 10.
- A high correlation factor can be observed between Class 1, 2, and 3 as they all have a bell-shape vehicle magnetic signature.
- Insignificant correlation factor was observed between classes other than Class 1, 2, and 3 .
- Change in vehicle trajectory will reduce the correlation factor between magnetic signatures for the same vehicle at different sites.

Thank you