



Optimization of Beam Loss Monitor Network for Fault Modes

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Requirement for Beam Loss Monitor Systems

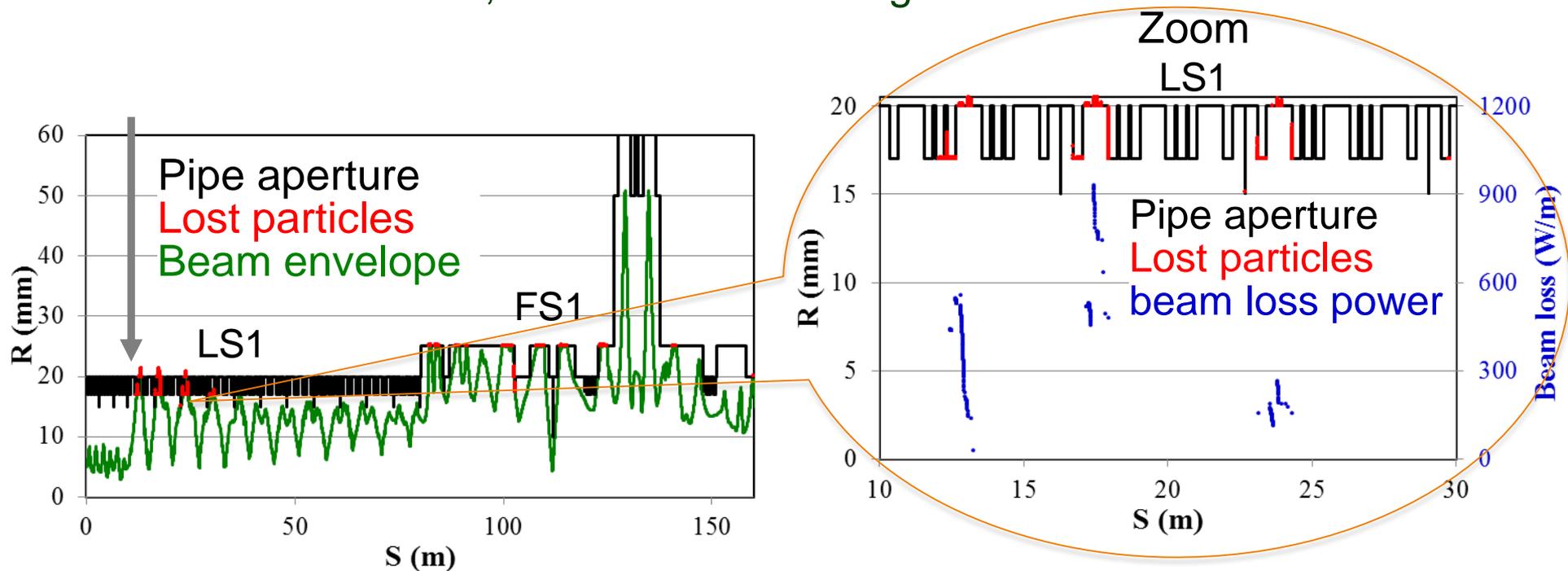
- Requirements for BLM network on machine faults can be categorized to two functions: fault detection and fault diagnosis.
- The *fault detection* function requires BLMs:
 - With fast response for big losses
 - Located around sensitive components to protect them
 - Located at “critical positions” to trigger MPS for fault modes
- The *fault diagnosis* function requires BLMs:
 - Sensitive enough to diagnose issues with beam tuning and slow losses
 - Able to differentiate between controlled and uncontrolled losses
 - Located at “discrimination points” to differentiate spatial loss patterns

Goal of BLM Network Optimization

- Find minimum # of BLMs required to trigger MPS for all fault modes, i.e. “**Critical Positions**”
 - Correlation Analysis between loss locations
- Find “**Discrimination Points**” to differentiate loss patterns from different error sources
 - De-correlation Analysis; Pattern Recognition
- Examples of implementation:
 - Single cavity failure mode at FRIB
 - Single solenoid failure mode at FRIB

Example Data of Simulated Loss Distribution

- In FRIB lattice, there are 572 “accelerator elements”, which can be considered as loss observation points in the simulation
- FRIB has 332 cavities, within which 241 failures result in beam losses. The resulted single-cavity-failure loss matrix is 572×241
- FRIB has 69 solenoids, and the resulted single-failure loss matrix is 572×69



Spatial Optimization for BLM Network

— Part 1

Looking for “critical positions” for each fault mode

- The ensemble of “critical positions” (CP) satisfies the following:
 - For every fault mode, the resulted loss can be detected by a small set of detectors at the “critical positions”
 - Need to quantify correlations between monitors for classes of events

Correlation Coefficient Matrix

- Correlation coefficient matrix $R_{n \times n}$ for matrix $X_{m \times n}$ is defined as

$$R(i, j) = \frac{\text{Cov}(X_i, X_j)}{\sigma(X_i) \cdot \sigma(X_j)}$$

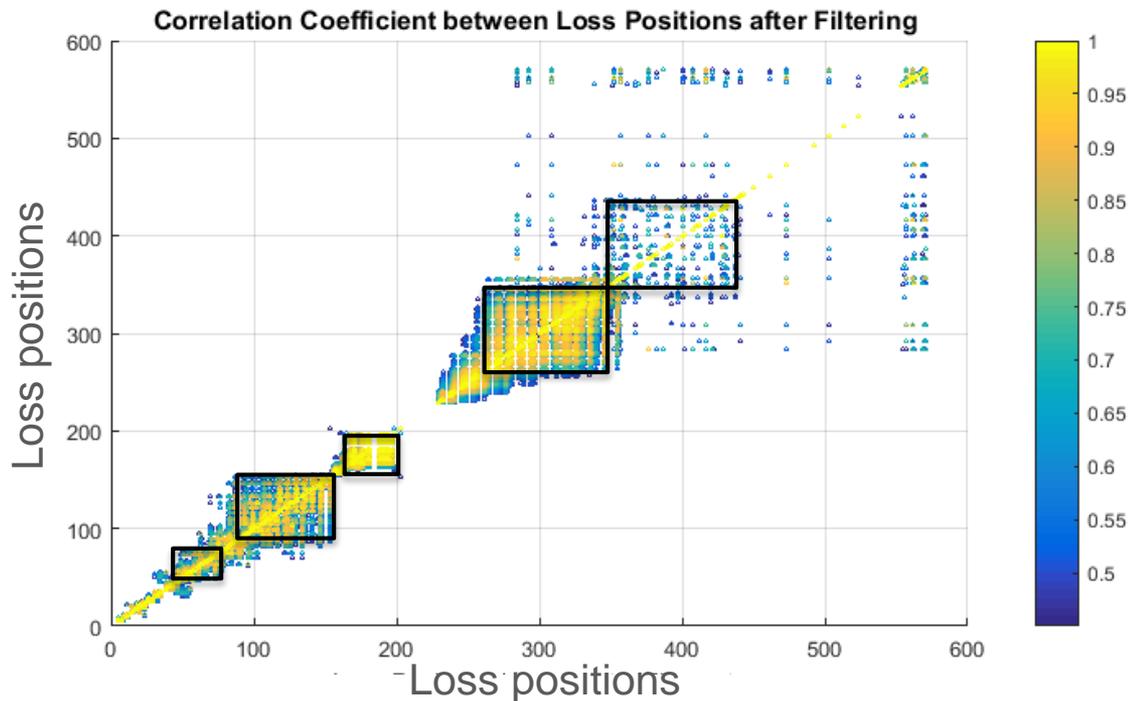
where $R(i, j)$ is the correlation coefficient of the i^{th} column and j^{th} column. Usually,

Correlation	Negative	Positive
None	-0.09 to 0.0	0.0 to 0.09
Weak	-0.3 to -0.1	0.1 to 0.3
Medium	-0.5 to -0.3	0.3 to 0.5
Strong	-1.0 to -0.5	0.5 to 1.0

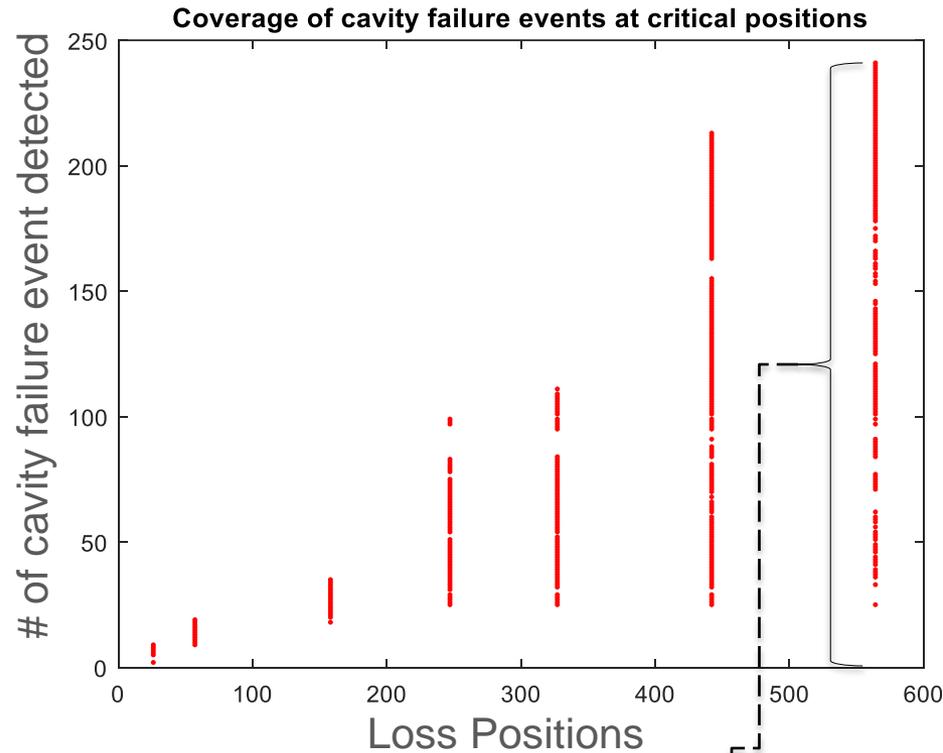
- For loss detection, we consider positions with positive strong correlation, e.g., ≥ 0.45 , as a group

Group Loss Points for Cavity-Failure Mode

- Zero out loss signals below MPS fast-trip threshold (defined as 10 W)
- Calculate position correlation matrix $R_{572 \times 572}$ for transposed loss matrix $X_{241 \times 572}$
- Exclude correlations less than 0.45 for better contrast



Check if the CP Ensemble Covers All Events



All 241 failure events are detected

- In the raw loss matrix $X_{572 \times 241}$, sum over each row (i.e. failure events) and sort the loss points in descending order of total loss, i.e., $(X_{\text{tot}})_{572 \times 1}$
- Starting with the largest loss, pick one CP in each correlated group, and a few CPs outside groups, i.e. [442, 564, ..., 247, ..., 327, ..., 57, ..., 158, ..., 26]
- Check if all 241 events are covered and add more CPs if needed

Spatial Optimization for BLM Network

— Part 2

Looking for “discrimination points” for each fault mode

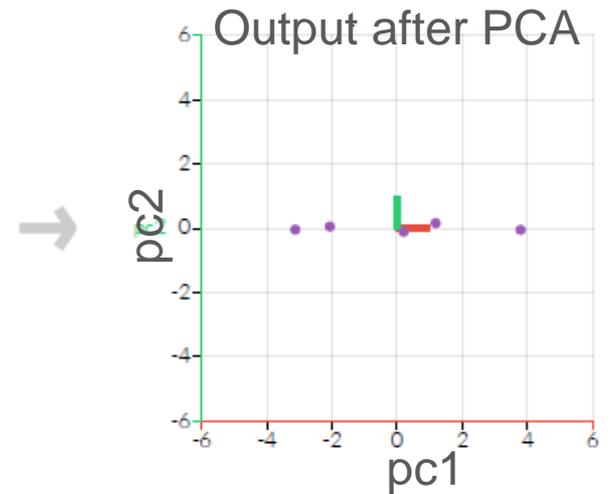
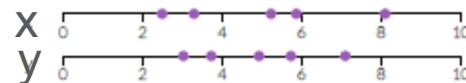
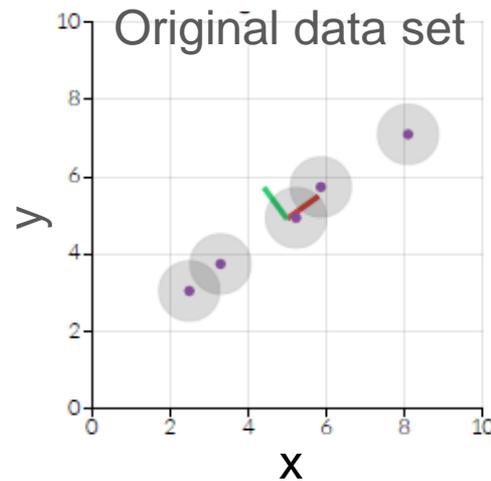
- The final goal is to construct
 - $P(\text{error-loss})$ — probability of error source, given an observed loss distribution
- Feature analysis as a theory of pattern recognition:
 - Recognition of significant features (discrimination points) rather than reading an exact template, for each fault mode
 - Contrasts/differentiates between failure events with distinctive features

Principal Component Analysis

- We introduce *Principal Component Analysis (PCA)* to find *significant features* for a fault mode and *distinctive features* to differentiate between failure events
- PCA is mathematically defined as an orthogonal linear transformation, $t_{k(i)} = X_{(i)} \cdot w_{(k)}$ in such way that the individual variables of t successively inherit the maximum possible variance from X , with each *loading* vector w constrained to be a unit vector

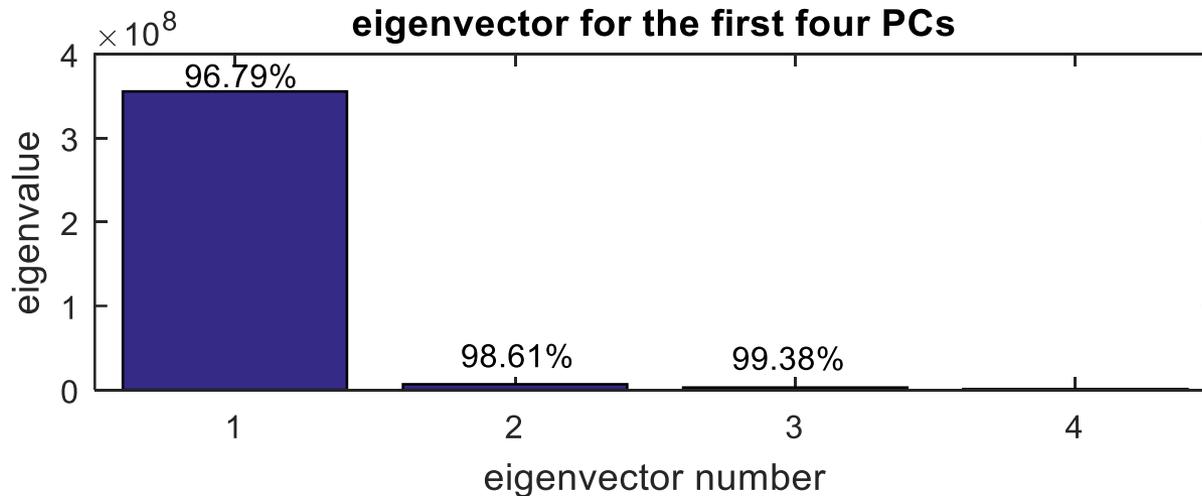
Example:

Each point could represent the loss at location x and y for a given failure event



PCA Analysis for Single-Cavity-Failure Mode

- PCA is good at dimensionality reduction (e.g. image compression)
- In this example, 97% of the variance in the data is accounted for by the first principal component, ~99% in total by the 1st and 2nd PCs.
- A dramatic reduction in analysis dimensionality from 572 to 1 or 2! The cavity failure events/patterns will achieve maximum variation on PC1.

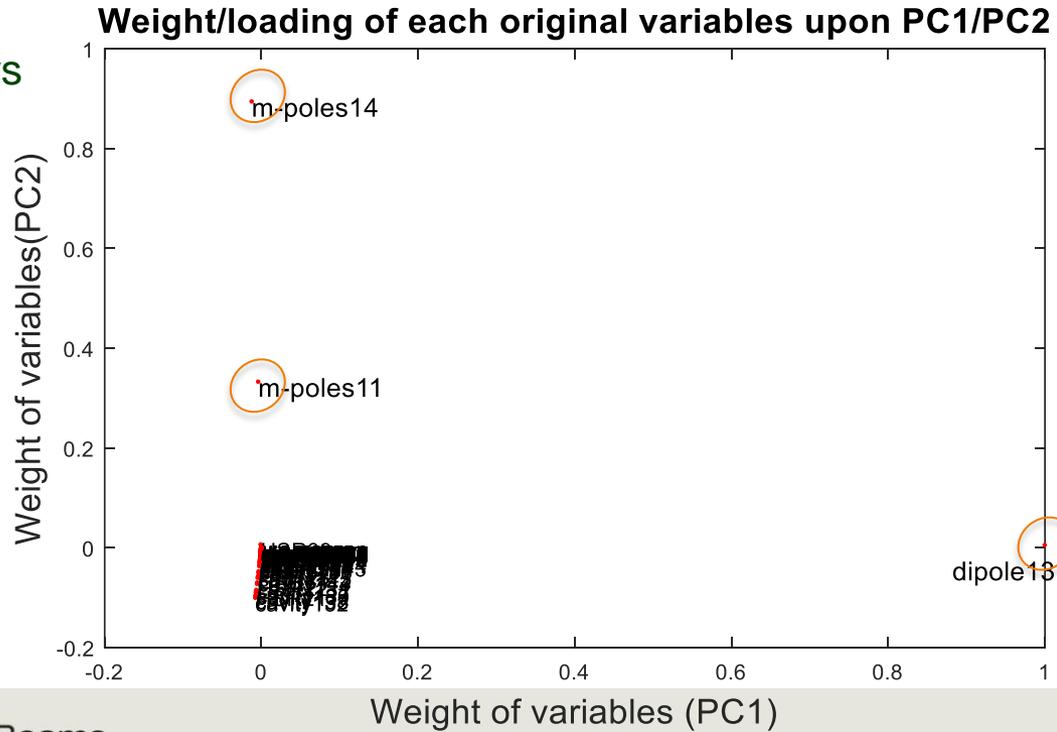
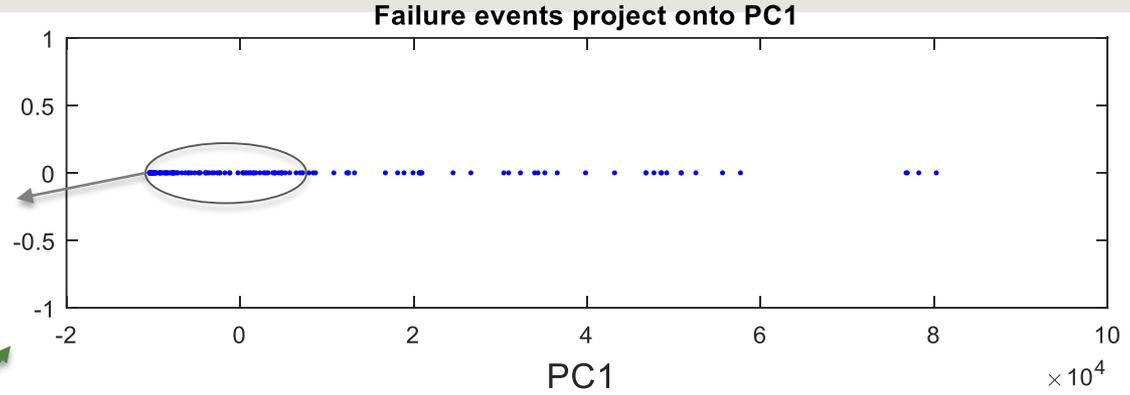


Extract Significant Features for Single-Cavity-Failure Mode

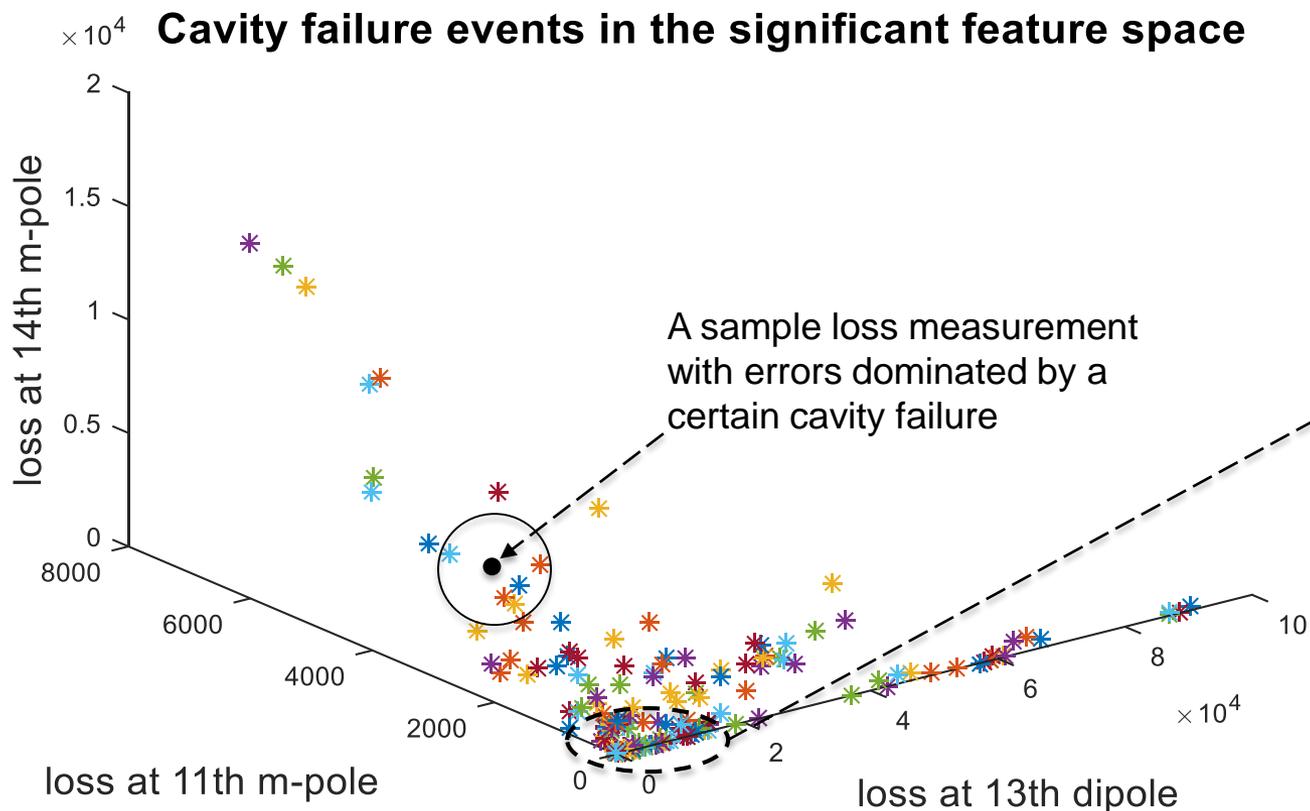
To further distinguish these events, exclude the *significant features* and re-do PCA for more *distinct features*. Repeat until most patterns are distinguishable.

- The *score plot* suggests potential clusters forming on the PC1. The more distance between points (e.g. failure events), the easier to distinguish them on PC1.

- The *loading plot* shows that 3 loss locations account for major difference between cavity failure events. These are significant features for the cavity fault mode, or “discrimination points” where BLMs should be placed.



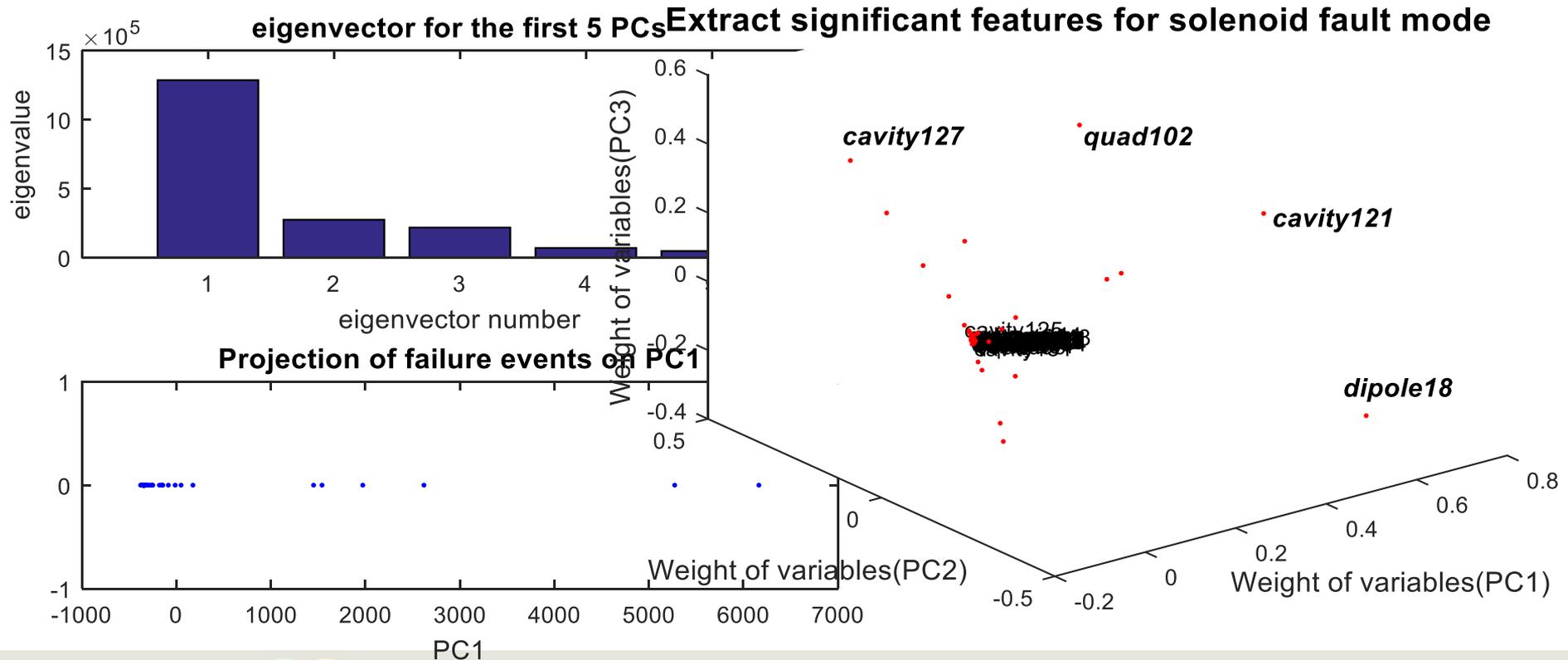
Pattern Distinction in Significant Feature Space



To further distinguish these points (e.g. failure events), we need to exclude the significant features from the raw data and re-do the PCA. Repeat this to get distinctive features for most patterns.

Extract Significant Features for Single-Solenoid-Failure Mode

- The “significant features” seem to be dipole 18, quad 102, cavity 121 & 127
- Dipole 18 is very close (~ 1 meter) to the 11th multipole, from the perspective of radiation detection. Therefore they can be considered as an overlapped feature for radiation signals.



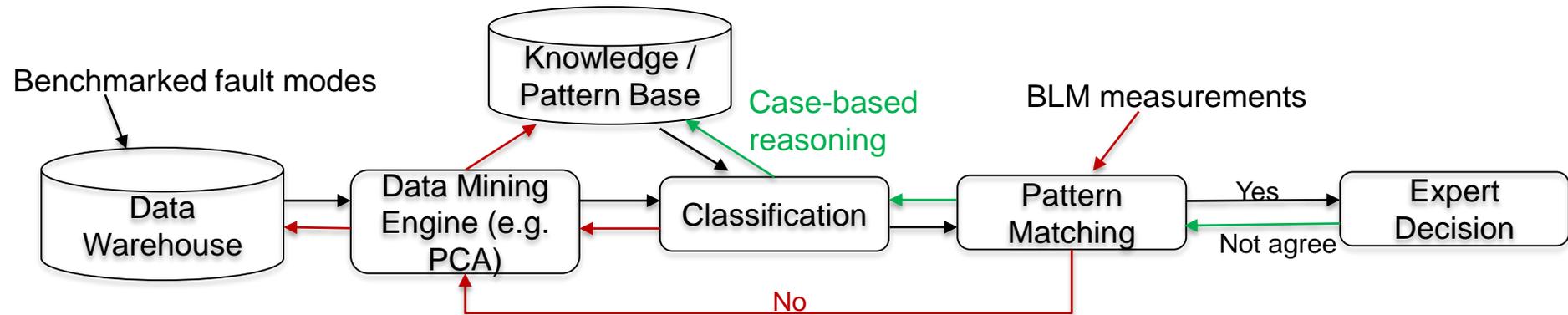
Conclusion

- We defined the spatial optimization goals for BLM network
 - Located at “critical positions” for fault modes
 - Located at “discrimination points” for loss pattern recognition
- We demonstrated how to locate “critical positions” for single-cavity-failure mode, by computing and grouping the correlation coefficient of loss positions
- We demonstrated how to use PCA to extract significant features for fault modes (e.g. cavity-failure mode and solenoid-failure mode)
- If the observed loss patterns were in conformance with knowledge base, then the projections in the feature space would provide a probability for dominated error source (e.g. slide 12)



Fault Diagnosis for Accelerators – Path Forward

■ Fault diagnosis methodology



Benchmarked loss simulation: Simulated fault modes need to be benchmarked by BLM measurements during commissioning

■ The fault diagnosis methodology should work when:

- The loss pattern is dominated by one or two error sources (e.g. most Fast Protection System triggered losses)
- The loss pattern has distinctive features

Acknowledgement – thanks!

- Dong Liu, *PhD, FRIB Control Department*
- Rebecca Shane, *PhD, FRIB Diagnostics Group*
- Zhengqi He, *PhD, FRIB Physics Group*
- Qiang Zhao, *PhD, FRIB Physics Group*
- Steven Lidia, *PhD, FRIB Diagnostics Group*
- Xiaoying Pang, *PhD, LANL*



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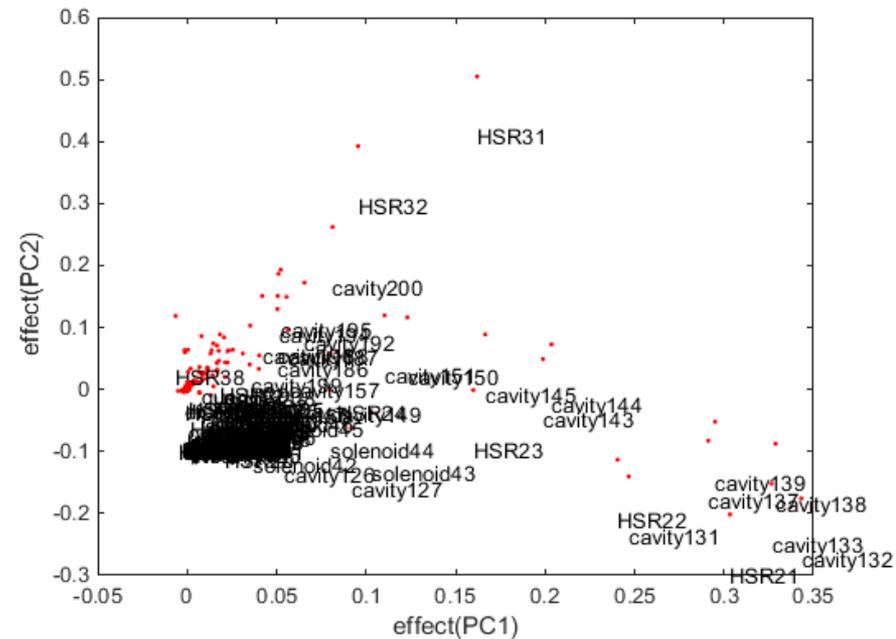
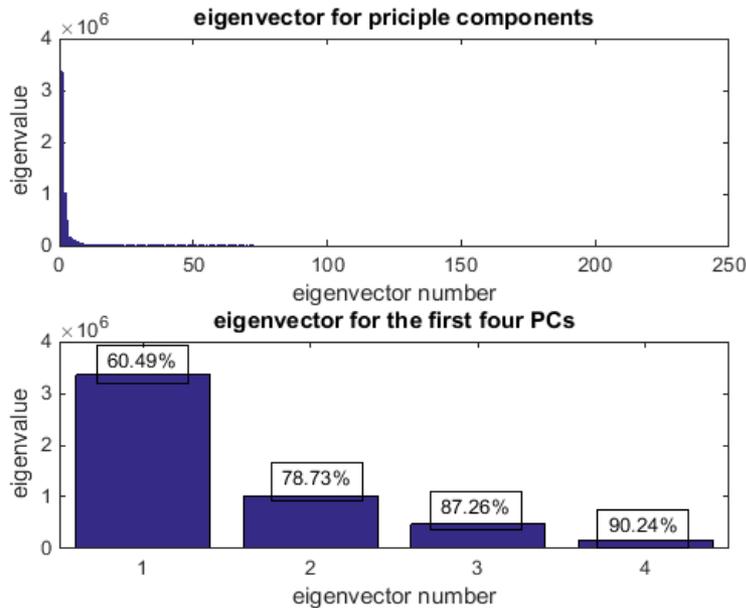
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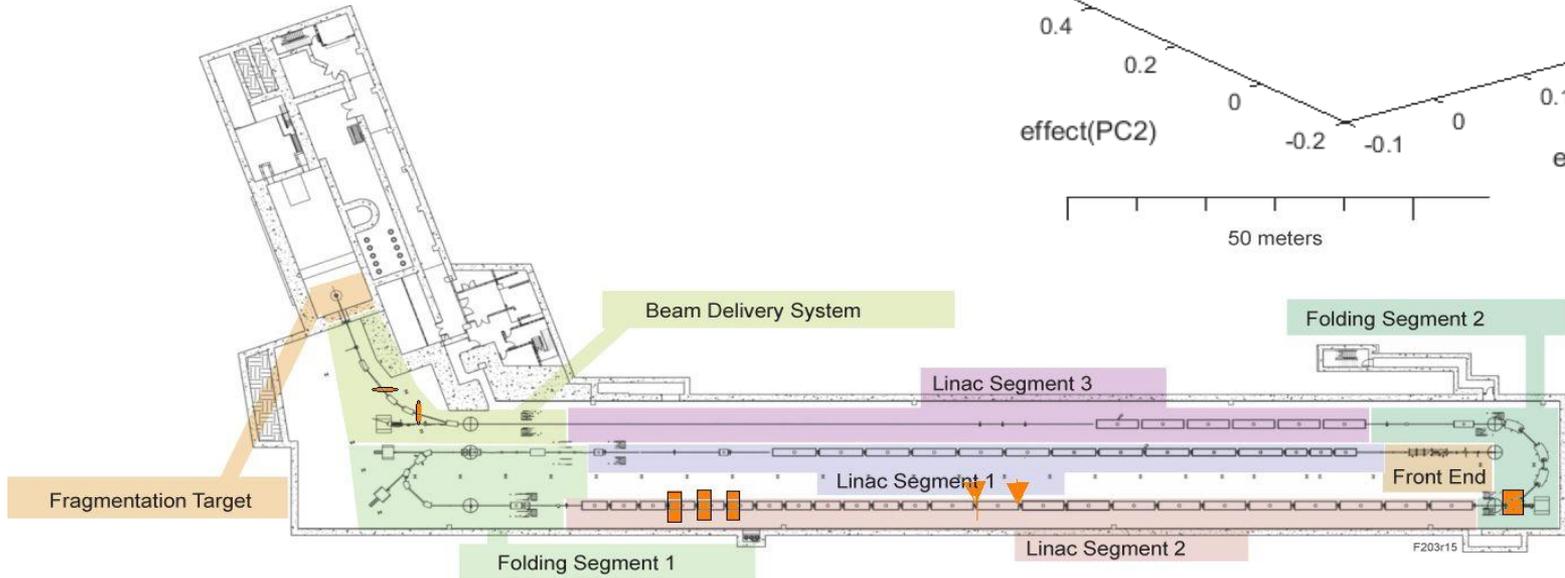
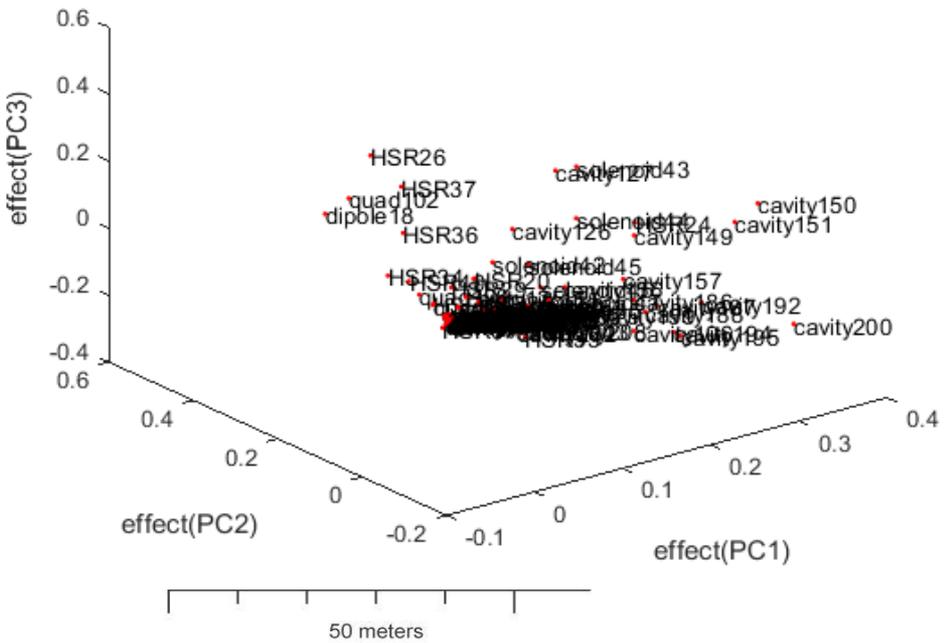
Repeat PCA Analysis for Cavity-Failure Mode

- To further allocate “*distrimination loss points*”, those 3 variables shall be excluded and a second PCA analysis needs to be performed on the rest of variables.
- The “critical loss points” from this step can be concluded as: 21st & 22nd & 23rd Halo Monitor Ring (HSR) and half of the cryomodule downstream of them respectively, as well as 31st & 32nd HMR.



3 Iterations of PCA Analysis for Cavity-Failure

- After one extra iteration to filter out HSR 38 and 39 as critical point, the critical point is not as obvious as before, and we can end there for cavity failure analysis.
- There are other fault modes that need to be analyzed respectively in the same way, such as solenoid failure.



A More Broad Feature Space Including Solenoid-Failure Mode

- FRIB has 69 solenoids. The loss distribution matrix correspondingly is 572×69 .
- We implemented two iterations of PCA analysis and mark the critical points from solenoid failure mode (green) together with cavity failure mode (orange).

