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Collaborative Filtering for Coordinated Monitoring in Sensor Networks

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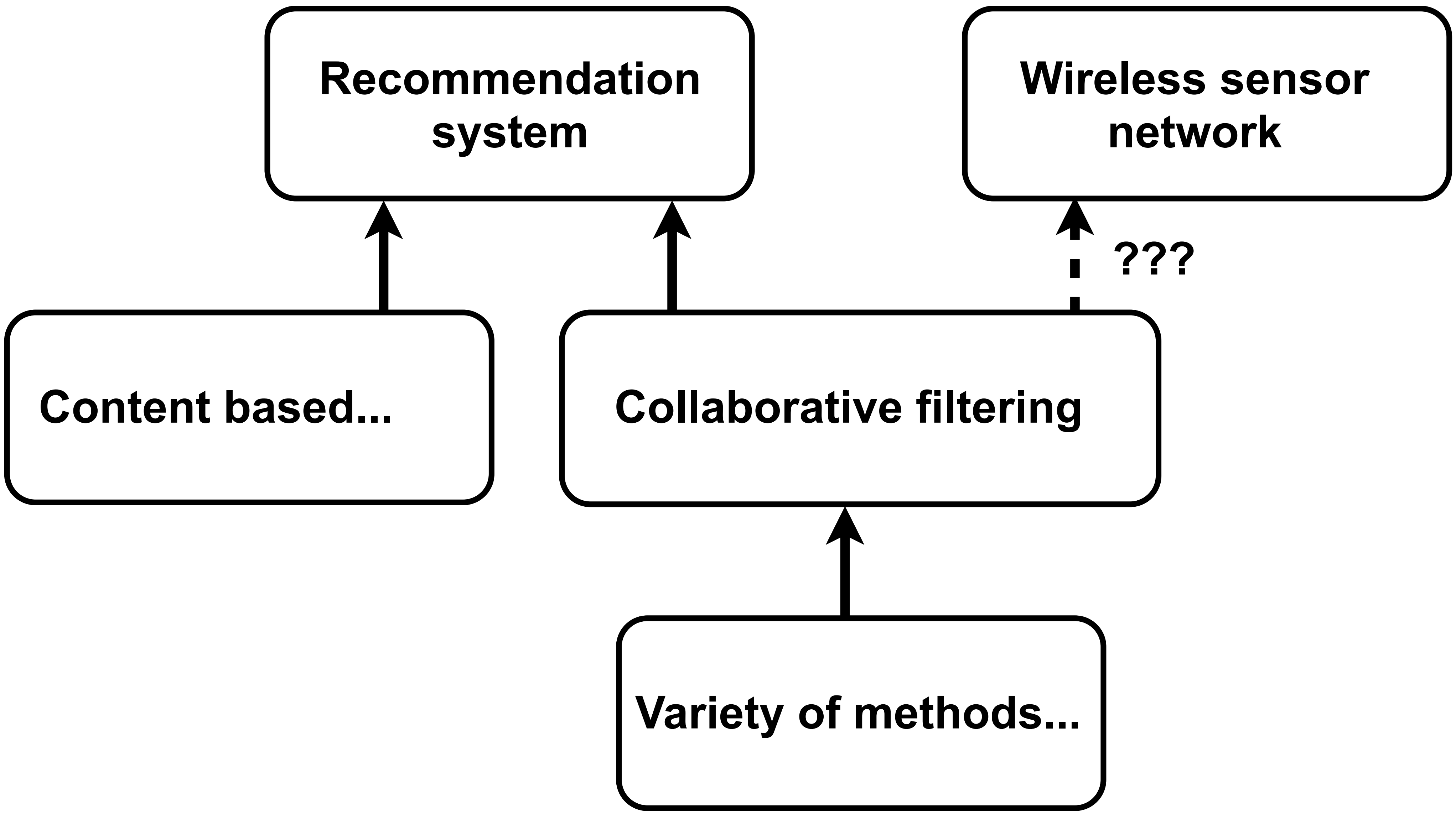
An idea...

- **Collaborative filtering useful in a wireless sensor network?**



Outline

- **Background**
  - Structural Health Monitoring (SHM)
  - Wireless Sensor Networks (WSN)
- **Coordinated monitoring problem**
  - Collaborative Filtering (CF)
  - Random assignment and Majority voting
- **Experiments and results**
  - Wooden model bridge
  - Aluminum bookshelf
- **Summary**

Background

- **Multidisciplinary research project**
  - Intelligent Structural Health Monitoring System (ISMO)
  - Applied mechanics, data mining, sensor networks...
- **Structural Health Monitoring**
  - Assessing the condition of man-made structures
- **Data mining**
  - Extracting relevant information from data
- **Wireless Sensor Networks**
  - Distributed computing environment

Structural health monitoring

- **No sensors that directly indicate damage**
  - Extracting features from vibration measurements
  - Sensitive to damages, not to environmental variability
  - *Transmissibility magnitude:* how well vibrations of certain frequency propagate between two sensors
- **Novelty detection problem**
  - Not allowed to damage the (unique) structure to collect training samples
  - Supervised feature selection not possible
  - Maybe some additional information available?

Wireless sensor networks

- **Eliminate costly and error-prone wires**
- **Restricted bandwidth and computation**
  - Simple features can be computed locally on a node
  - Number of transmitted features should be low
- **Each sensor node should concentrate on measuring relevant features!**
- **Relevance depends on what the other nodes are measuring => coordination problem!**

Coordinated monitoring

- **Monitor at most D local features / node**
  - An upper limit on computation & communication
  - Sparsity helps also the detection algorithm
- **Each local feature can be given a rating**
  - Encodes *additional application-specific information*
  - The above restriction holds: only D ratings at a time
- **Computation of combined features**
  - Requires measuring certain sets of local features
  - Local ratings combined to select monitored features

Collaborative filtering

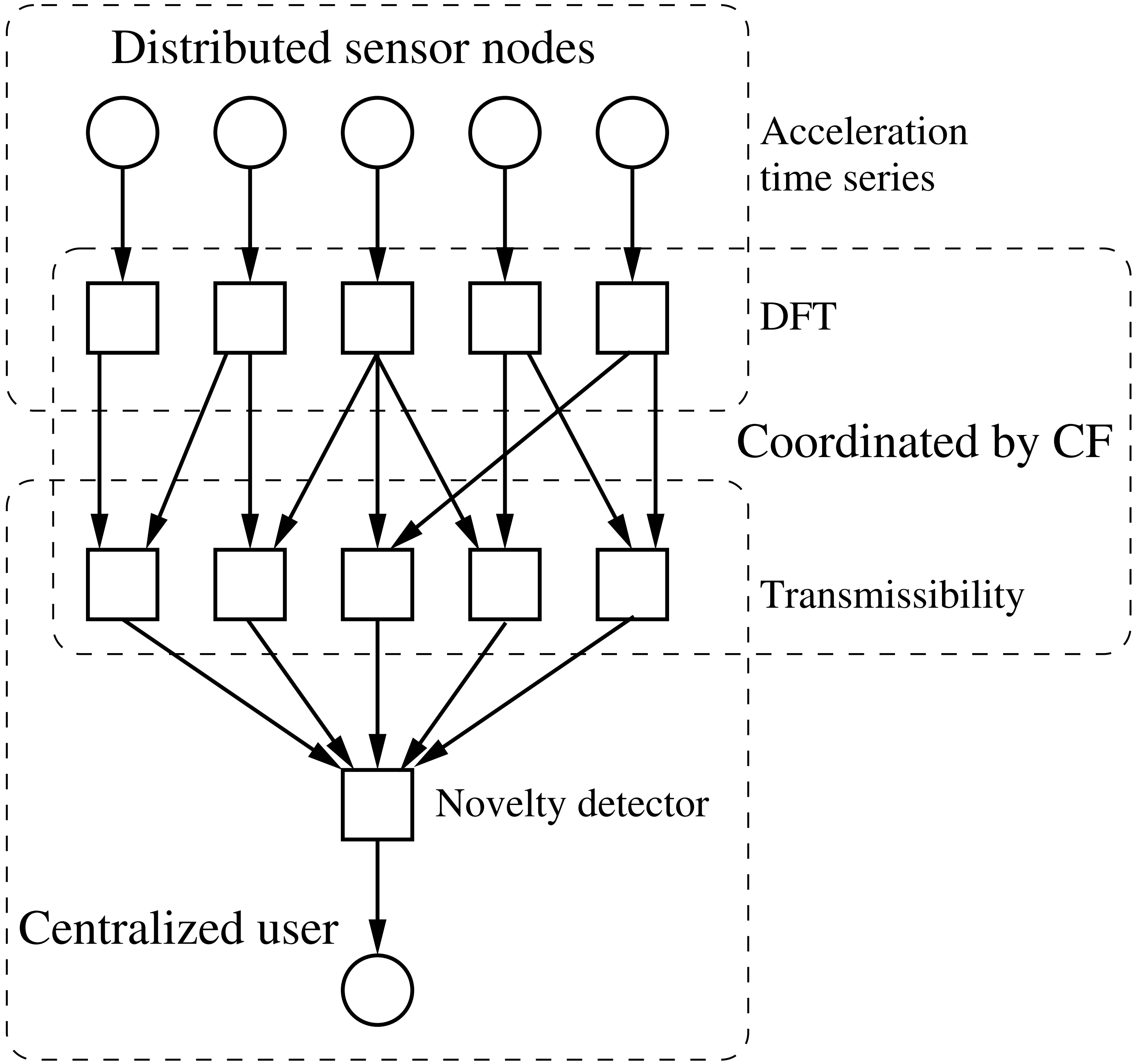
- **Traditionally in recommendation systems**
  - *Users* give ratings to *items*
  - Recommend new items to a user based on ratings from other similar users
- **Assumes structure in the rating data**
  - Similar users like prefer same items
- **Needs to deal with the sparsity of ratings**
- **WSN: recommend features to nodes!**
  - some similarities & differences to conventional CF...

Baseline: random & voting

- **What if it doesn’t matter which features to monitor / all are equally good?**
  - Let’s try also random selection, at most D/node
- **What if the sensors don’t need to specialize / just one global choice enough?**
  - Let’s try majority voting based on the same ratings
  - Number of combined features may still be high due to the number of combinations...

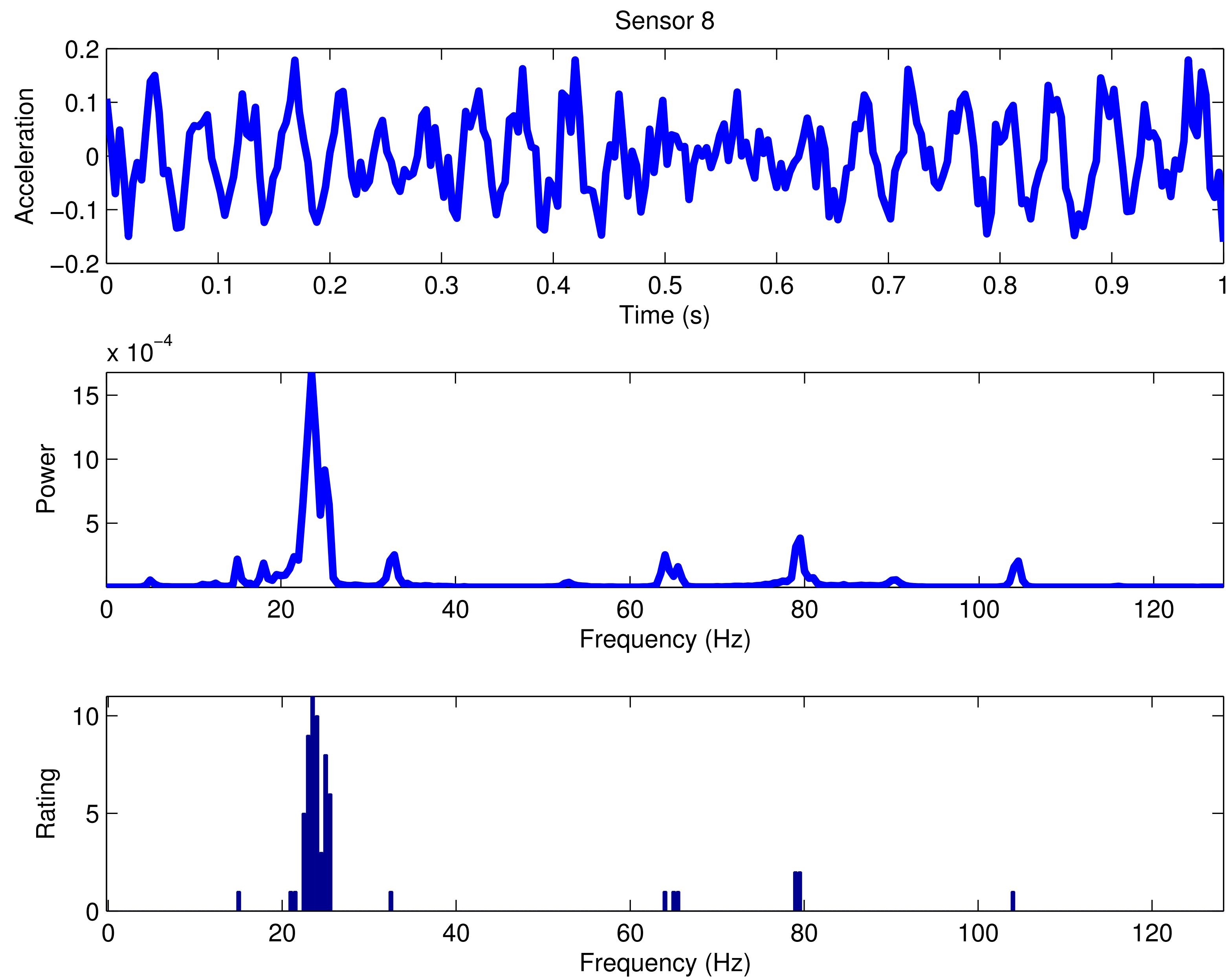
The proposed architecture

- **Accelerometers:**
  - time series $x_s[n]$
- **Local features:**
  - power spectrum $X_s[k]$
- **Combined features:**
  - transmissibility $T[s_1,s_2,k] = X_{s1}[k] / X_{s2}[k]$
- **Novelty detector: k-NN or Gaussian**



Frequency domain ratings

- **Mean power spectrum $X_s[k]$**
  - run FFT etc.
  - over *t* time windows

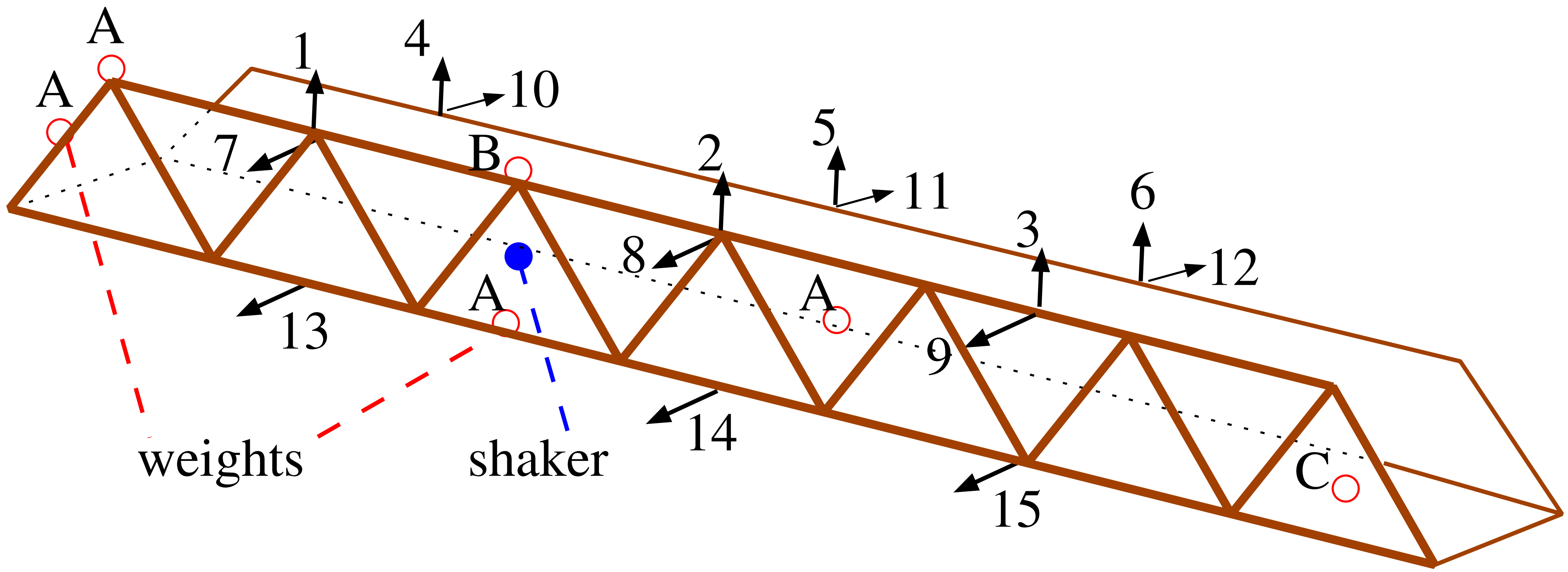


- **Sort by power**
- **For top-D bins**
  - $r[s,k] \mathrel{+}= 1$
  - Default vote 0
- **Repeat M_{CF} times**

Combined ratings and CF

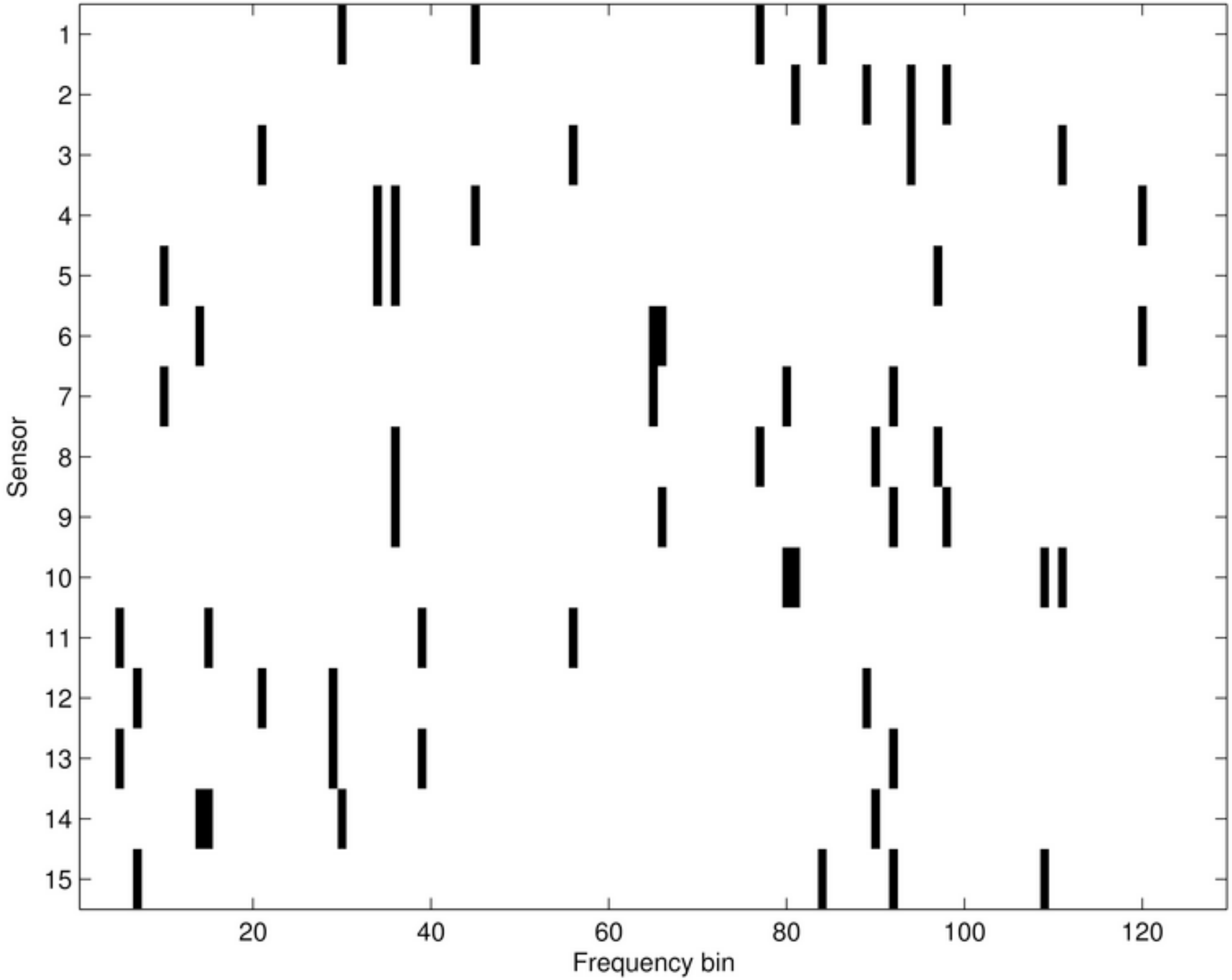
- **After collecting local ratings *r[s,k]***
- **Compute ratings for the combined features**
  - $w[s_1,s_2,k] = corr_j(r[s_1,j], r[s_2,j]) * r[s_1,k] * r[s_2,k]$
  - similarity of sensors s_1 and s_2 measured by correlation
  - symmetric, since transmissibility is ”symmetric”
- **Sort and select top-D combined features for each sensor node**
  - some sensors may be left with less than D features, if other nodes are fully utilized
  - no eliminated items like in recommendation systems

Data: Wooden bridge [19]

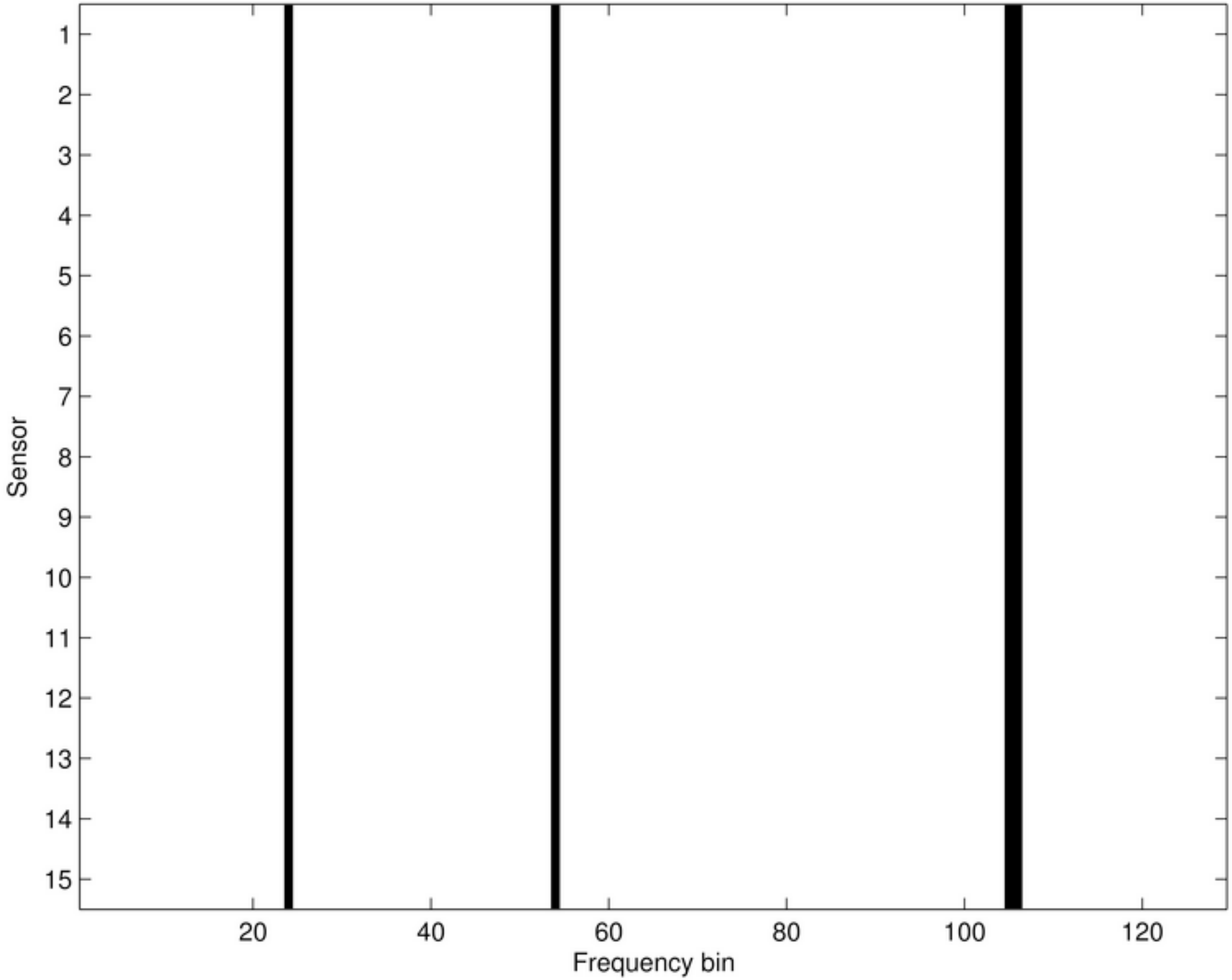


- **15 accelerometers and a shaker**
- **Added weights to simulate damages**
- **1998 + 265 time series measurements**
  - 32 seconds • 256 Hz = 8192 samples each

Example: Random, D=4



Example: Majority vote, D=4



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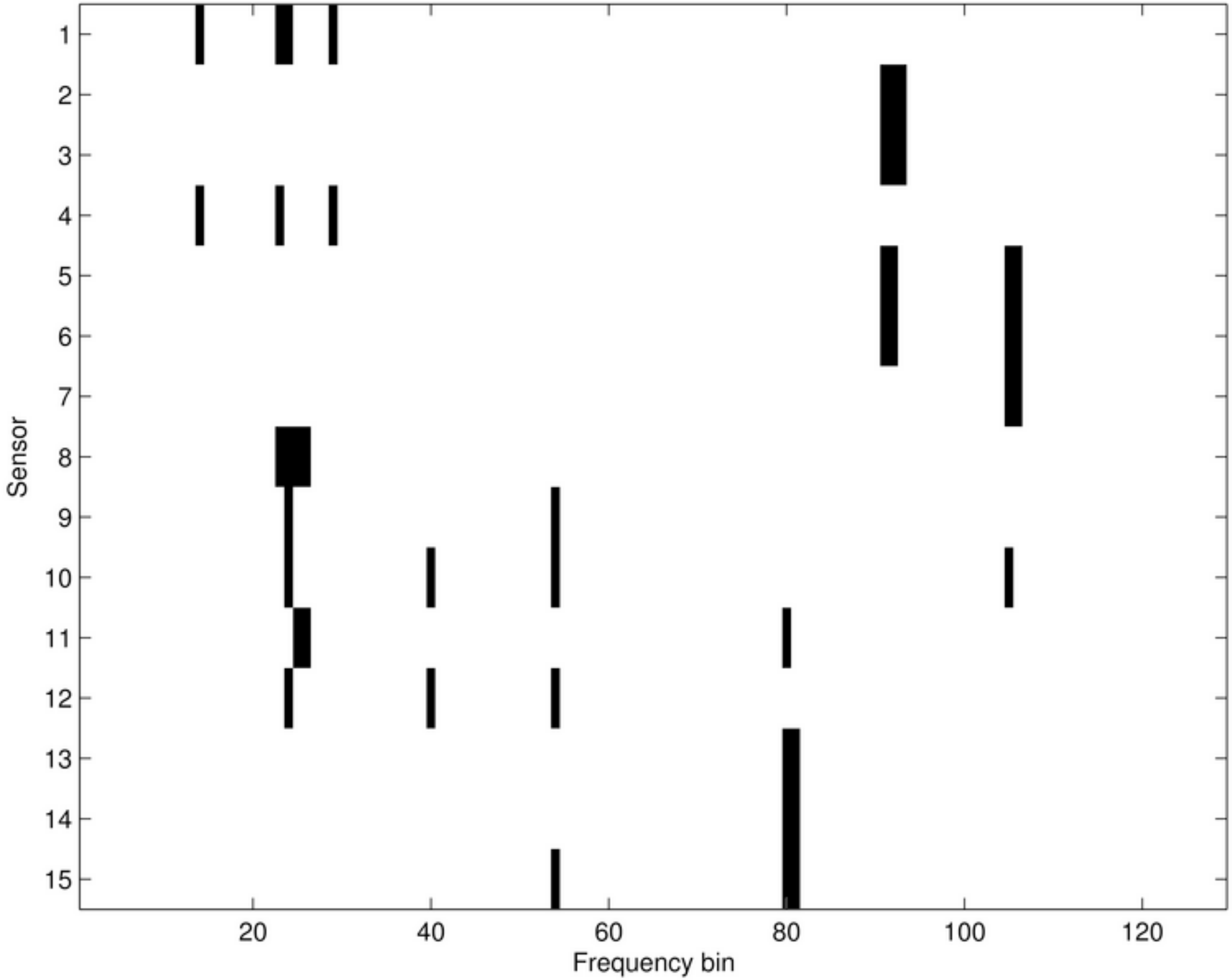
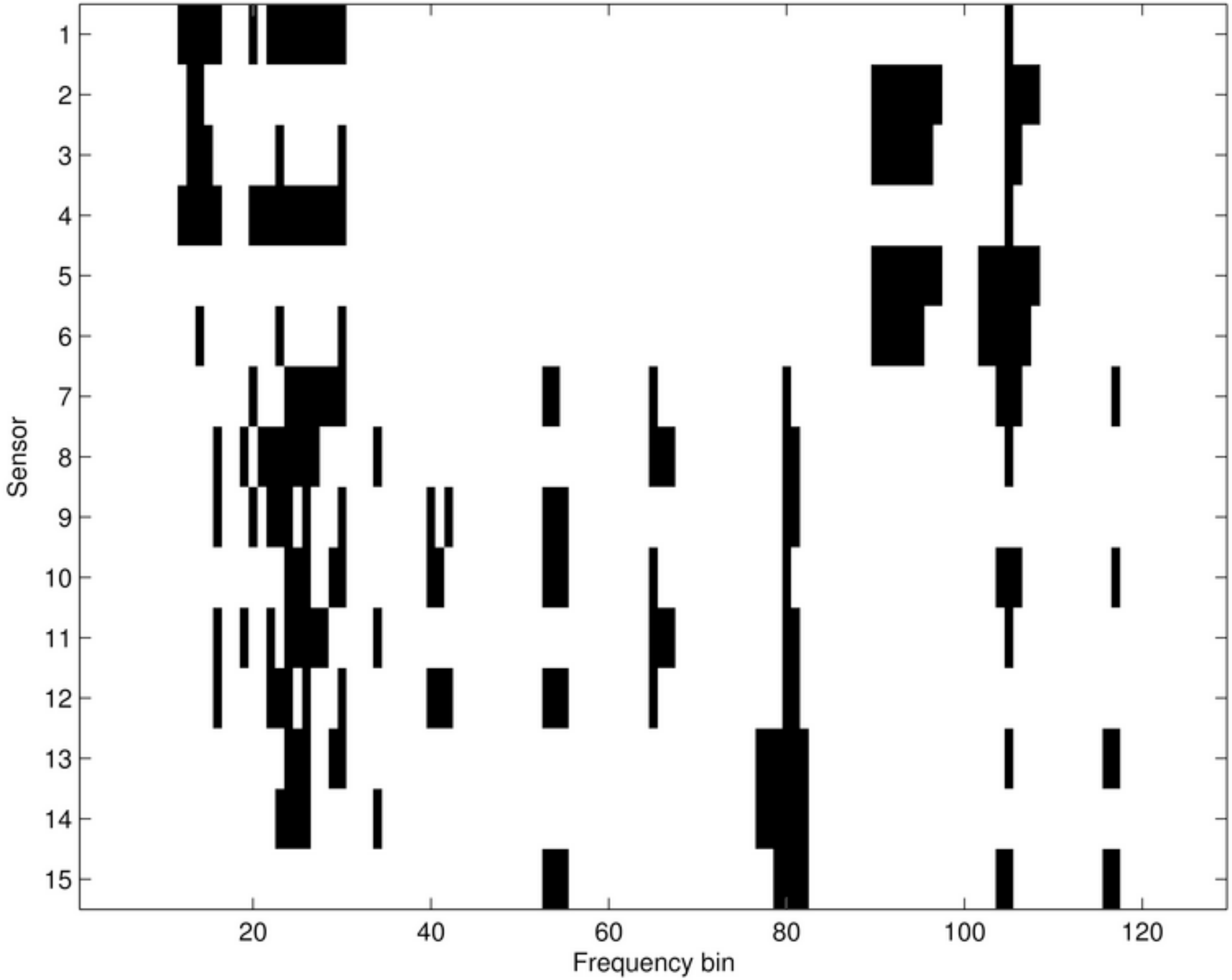
Example: CF, D=4

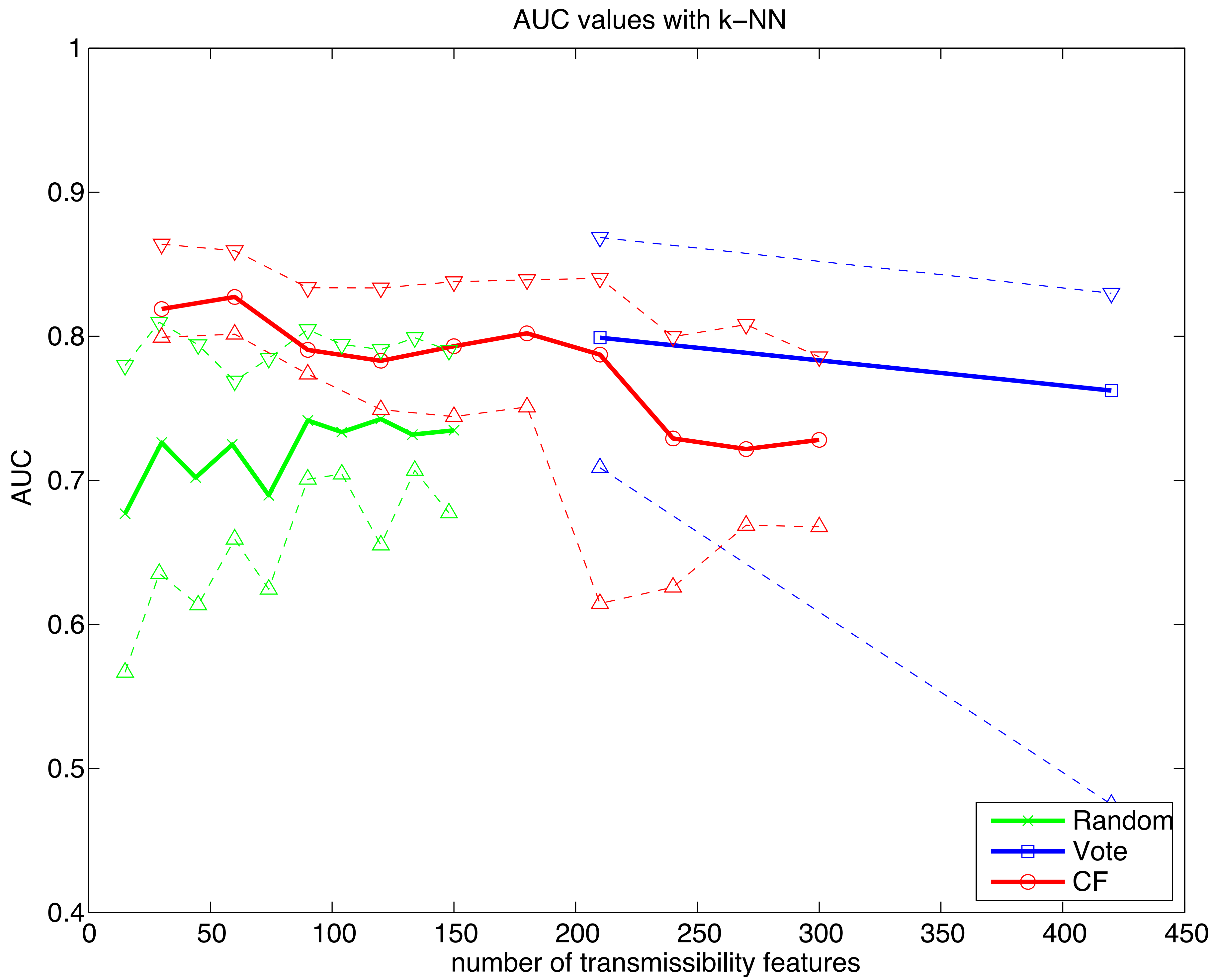


Example: CF, D=20



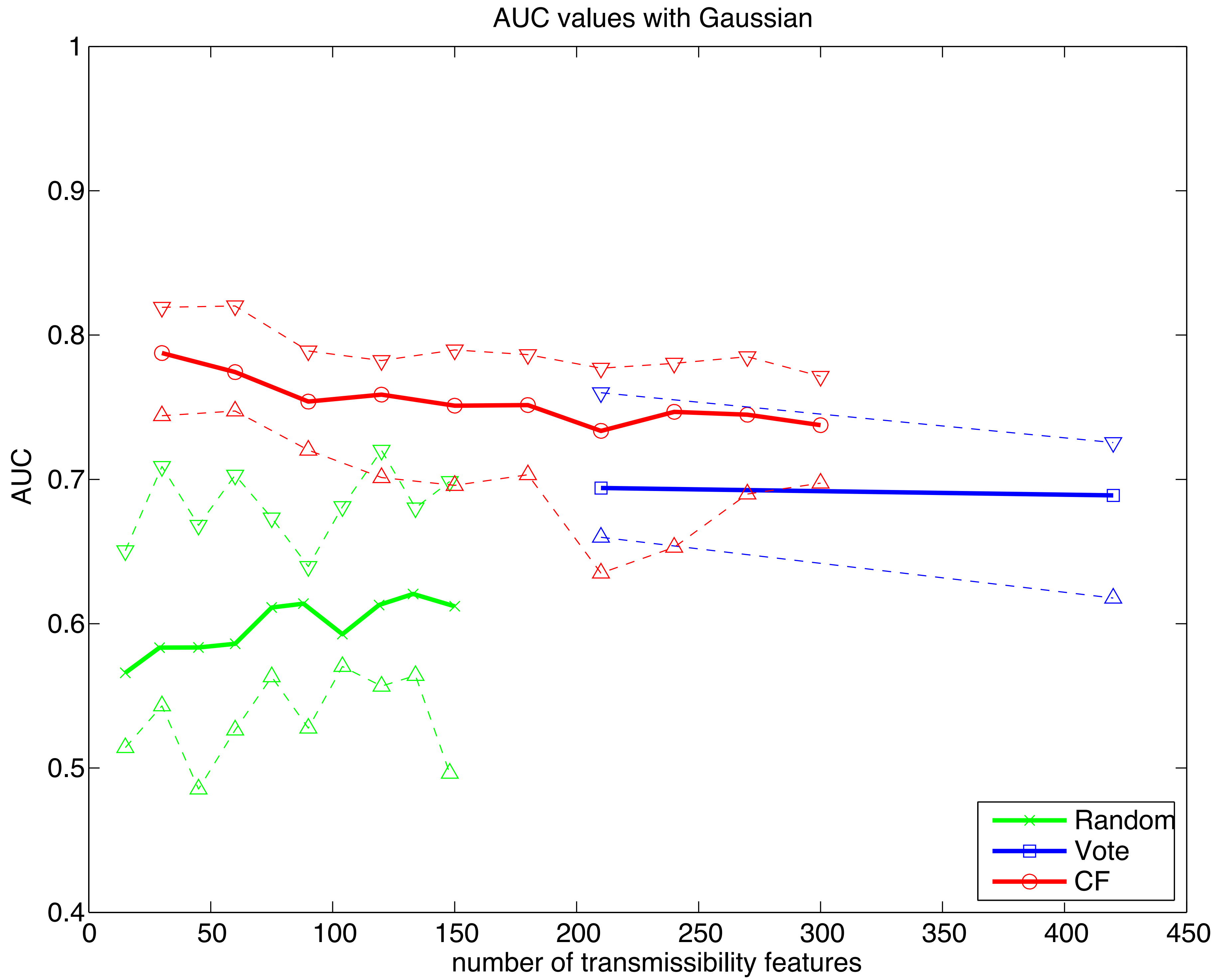
Novelty detection accuracy

- Iterated 10 times
- CF, vote, random
  - D=2...20
- k-NN detector
  - min, med, max AUC

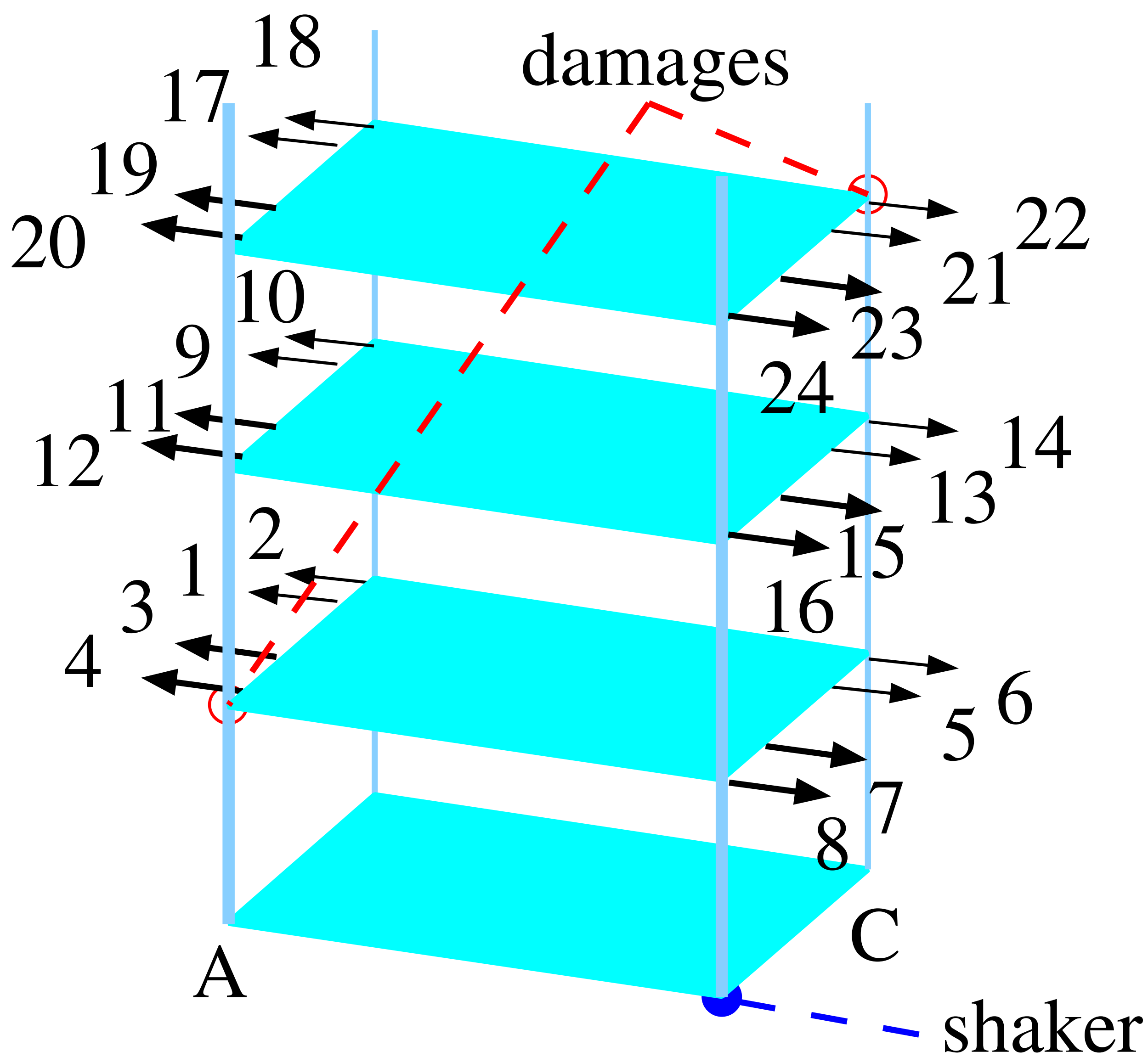


Novelty detection accuracy

- **Iterated 10 times**
- **CF, vote, random**
  - **D=2...20**
- **Gaussian detector**
  - **min, med, max AUC**



Data: LANL bookshelf [20]



- 24 accelerometers
- Loosened and removed bolts
- Shaker at the bottom
- 150 + 120 time series measurements
  - 5.12 sec • 1600 Hz = 8192 samples each

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Novelty detection accuracy

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- CF, vote, random
  - D=2...20
- k-NN detector
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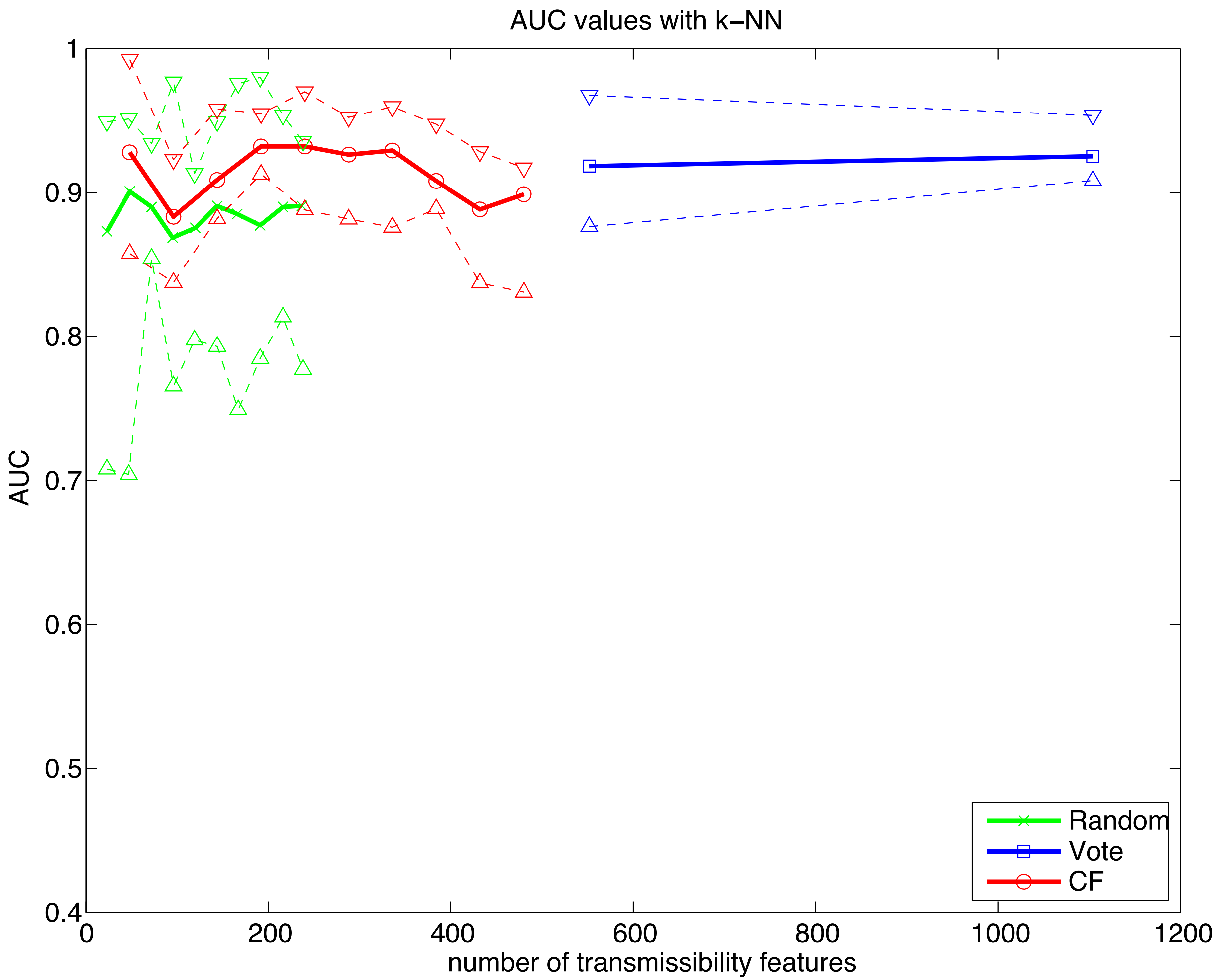

Novelty detection accuracy

- **Iterated 10 times**
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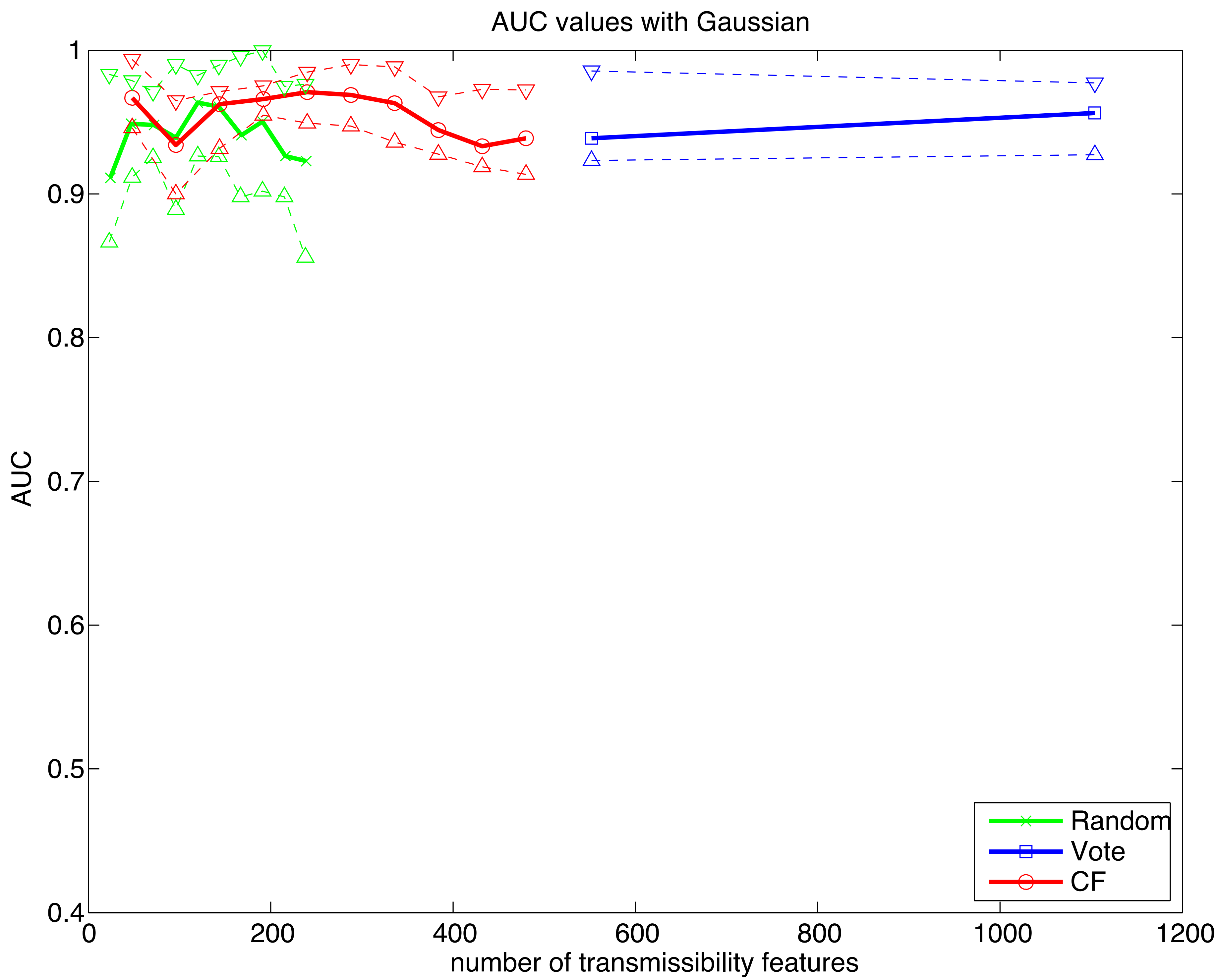

Summary

- **Problem of coordinated monitoring**
- **Collaborative filtering as a solution**
- **Applied as part of SHM system**
- **Demonstrated with two data sets**
  - 8192•S acceleration samples => one detection result
  - CF performed well with wooden bridge data
  - Differences smaller with the LANL bookshelf data
- **Some CF problems remain: coverage**