

6-7-2018



# First evaluation report



Esther Robb  
Project Website: [e-271.github.io](https://e-271.github.io)

# Completed in the first month

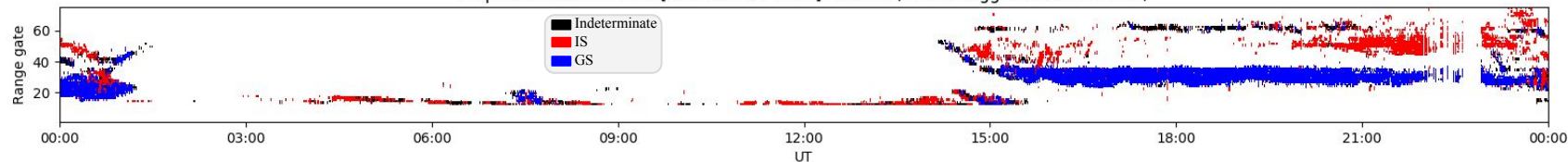
- Set up a project website and GitHub repository
  - [e-271.github.io](https://e-271.github.io)
  - [https://github.com/vtsuperdarn/clustering\\_superdarn\\_data](https://github.com/vtsuperdarn/clustering_superdarn_data)
- Create poster for presentation at 2018 SuperDARN Workshop
  - [https://e-271.github.io/docs/robb\\_superdarn\\_clustering.pdf](https://e-271.github.io/docs/robb_superdarn_clustering.pdf)
- Test out high-latitude and mid-latitude radars to compare Gaussian Mixture Model performance
  - Performance is similar on the day we tried (2-7-18)
- Study statistics of the data
  - Some data does not appear Gaussian, but PCA transformation helps (?)
- Select a good model (using BIC and forward-selection)
  - BIC: Found that GMM full covariance is best
  - Forward selection: Preliminary results unclear, more research is needed

# Demo: Project setup and running scripts

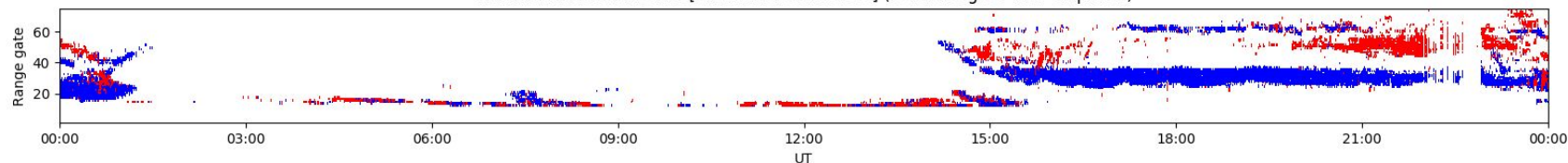
# Comparing mid-latitude and high-latitude

Saskatoon 2-7-18

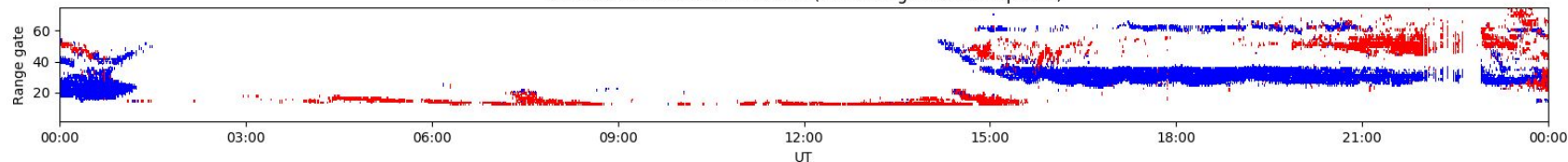
Empirical Model Results [Burrell et al. 2015] Beam 7 (7.93% flagged indeterminate)



Traditional Model Results [Blanchard et al. 2009] (92.07% agree with empirical)



Gaussian Mixture Model Results (86.69% agree with empirical)

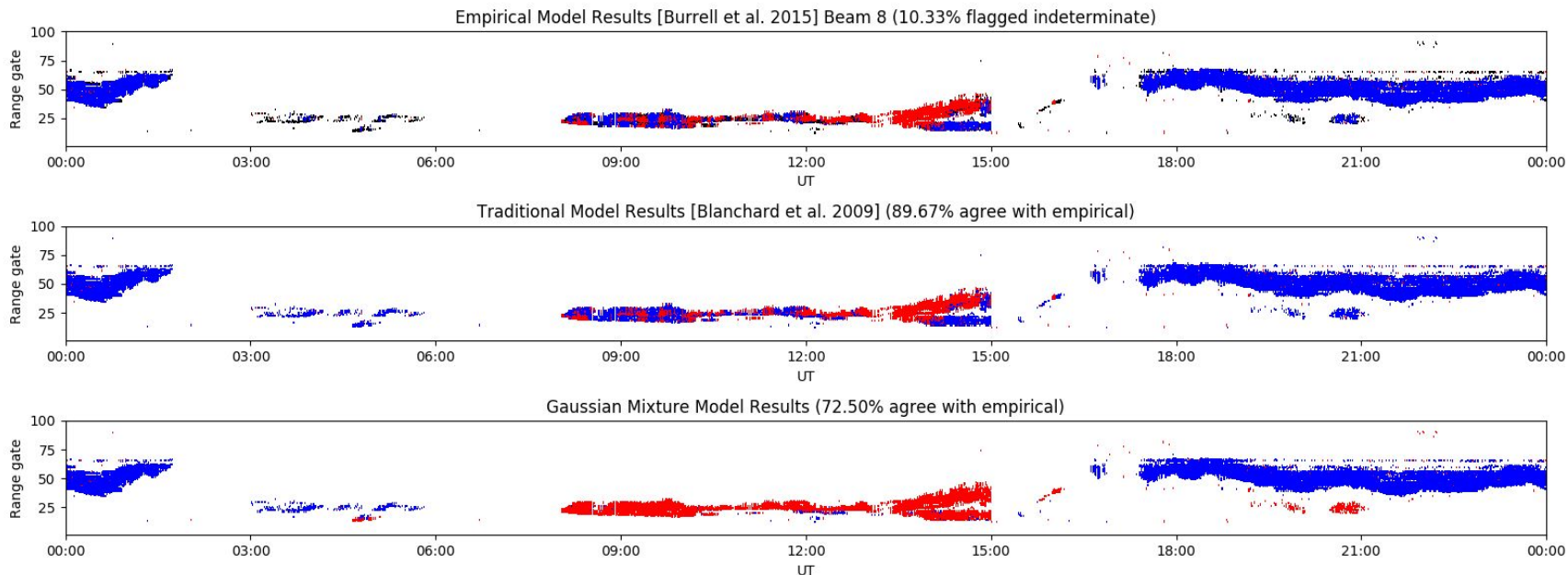


## High-latitude

- GMM is doing a good job
- Outliers get clustered together and misclassified
- Need to find a way to better capture outliers

# Comparing mid-latitude and high-latitude

CVW 2-7-18



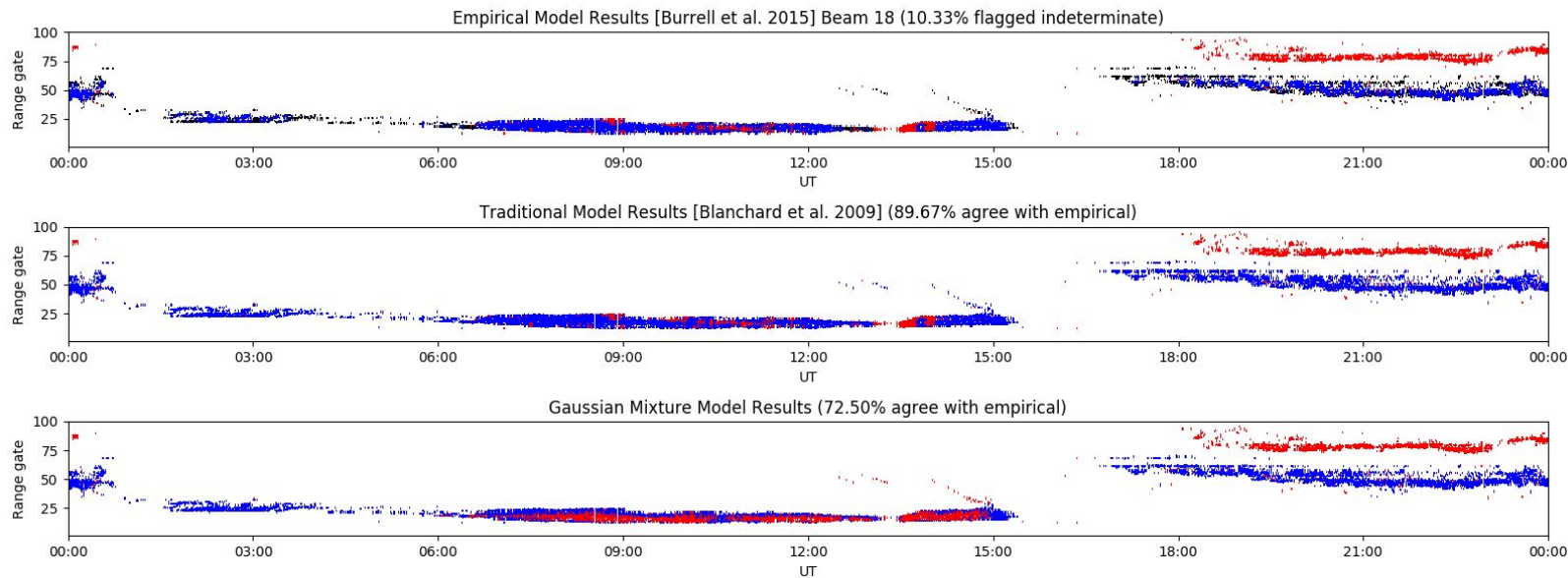
## Mid-latitude

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# Comparing mid-latitude and high-latitude

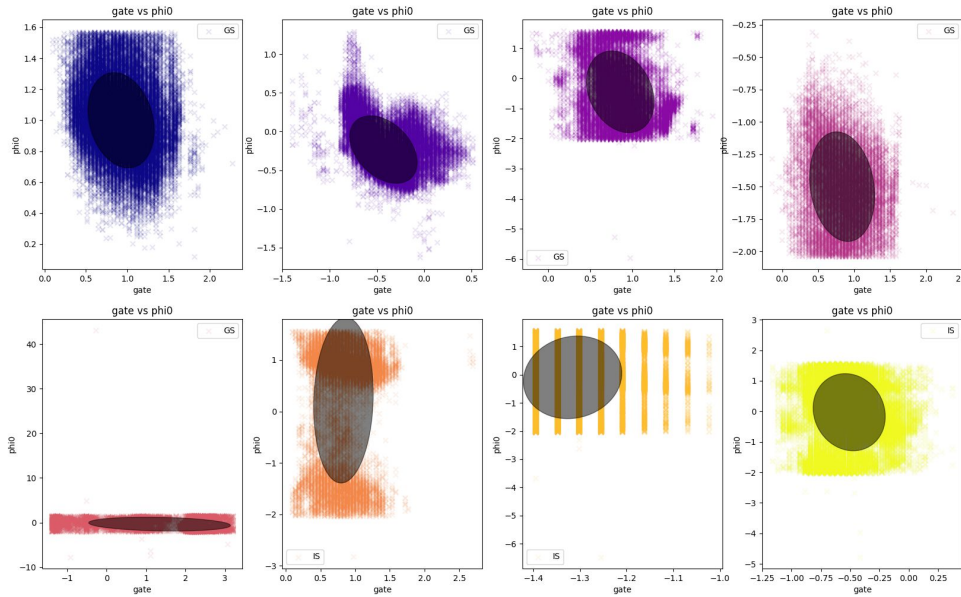
CVW 2-7-18



## Mid-latitude

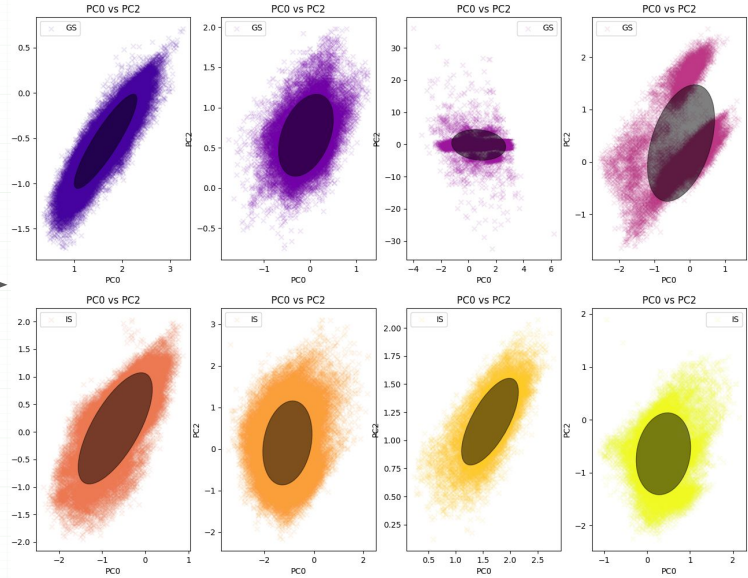
- GMM is doing a bad job (so is empirical model)
  - Likely low-velocity 0.5 hop IS
- Threshold should be adjusted

# Studying the dataset



- Some features don't look Gaussian
  - Phi0 (above), beam, power

PCA



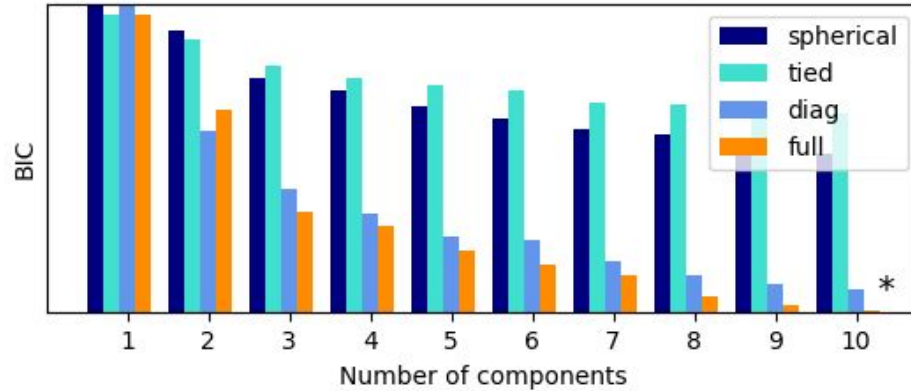
PCA transformation makes features look more Gaussian

- PCA does an axis transformation - so our data looks more Gaussian after axis change
- PCA tries to get rid of 'noise' by dropping lowest-variance axis - assuming 'signal' has high variance 'noise' has low variance

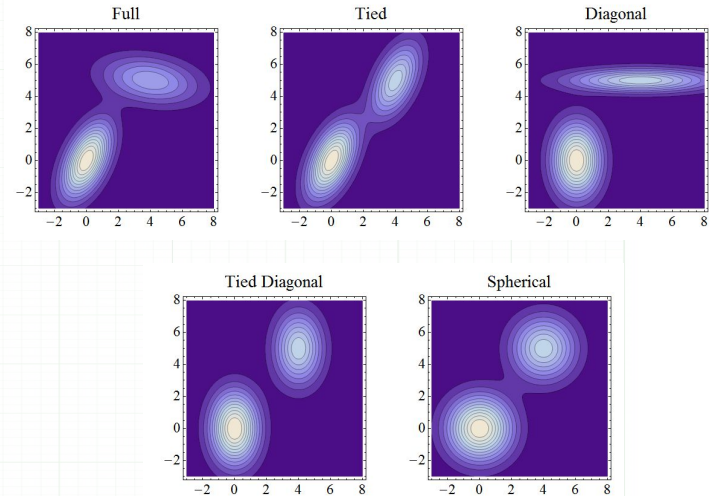
# Selecting GMM covariance type (BIC)

BIC for different covariances, # clusters

Selected GMM: full cov, 10 components



GMM Covariance types



Running BIC with different covariance types found that full covariance is best



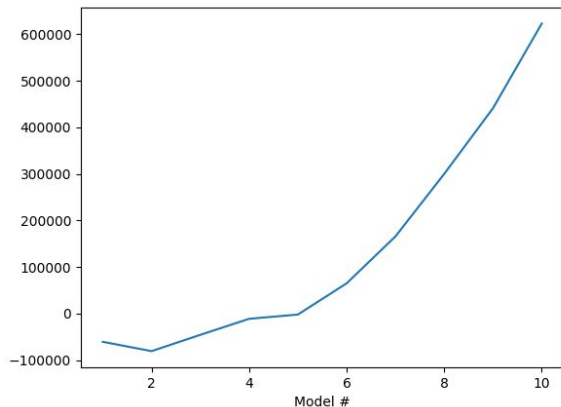
# Next Steps

- Study a few days worth of data and use human expert analysis as 'ground truth' to:
  - Compare different GMM models
  - Adjust the threshold
    - Test out Ribiero method, test an adjustment of the traditional method
  - Test results of removing non-Gaussian features
    - Beam and power are low importance on all tests, sometimes  $\phi_0$
  - Test transformations to capture edge behavior

Thank you!

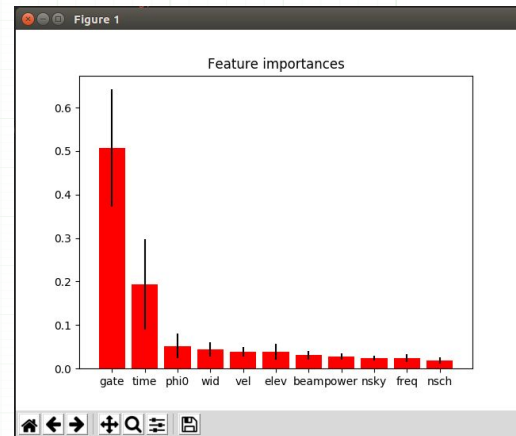
# Selecting features/clusters (forward selection)

CVW, 2/7/18, beam 12



- Used 50 as max # of clusters

Model #	Features	# Clusters	BIC
1	Freq	9	-60,929
2	Freq, time	20	-80,932
3	Freq, time, nsky	35	-45,856
4	Freq, time, nsky, phi0	50	-11,452
5	Freq, time, nsky, phi0, elev	45	-2,317
6	Freq, time, nsky, phi0, elev, nsch	50	64,805
7	Freq, time, nsky, phi0, elev, nsch, gate	50	165,587
8	Freq, time, nsky, phi0, elev, nsch, gate, power	25	299,981
9	Freq, time, nsky, phi0, elev, nsch, gate, power, wid	25	441,036
10	Freq, time, nsky, phi0, elev, nsch, gate, power, wid, vel	20	623,056

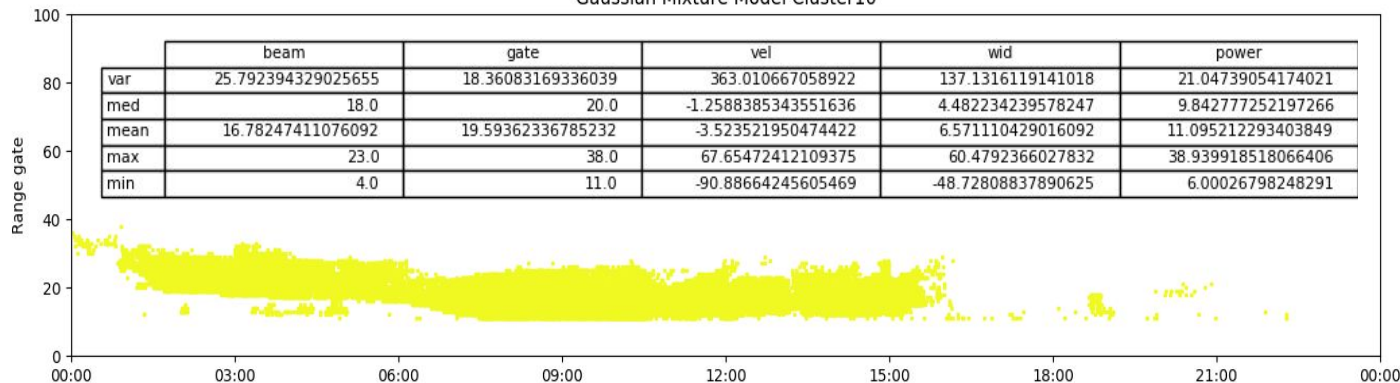


The old feature selection method

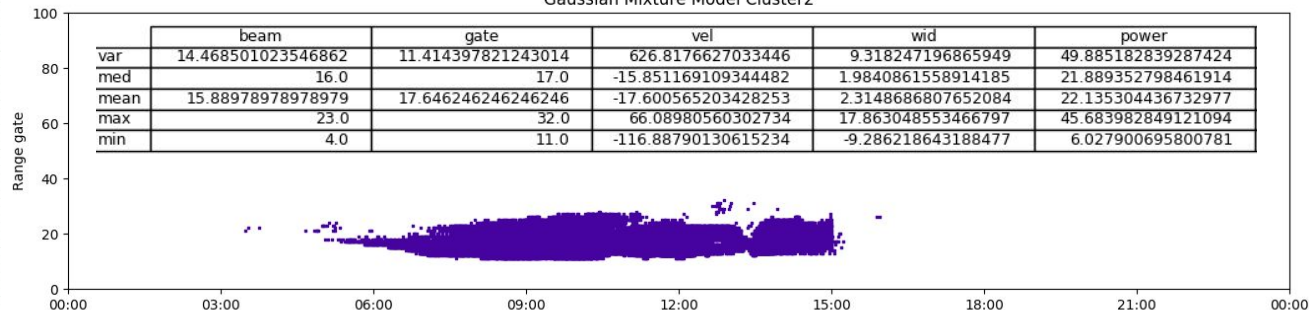
# Comparing mid-latitude and high-latitude

CVW 2-7-18

Gaussian Mixture Model Cluster10

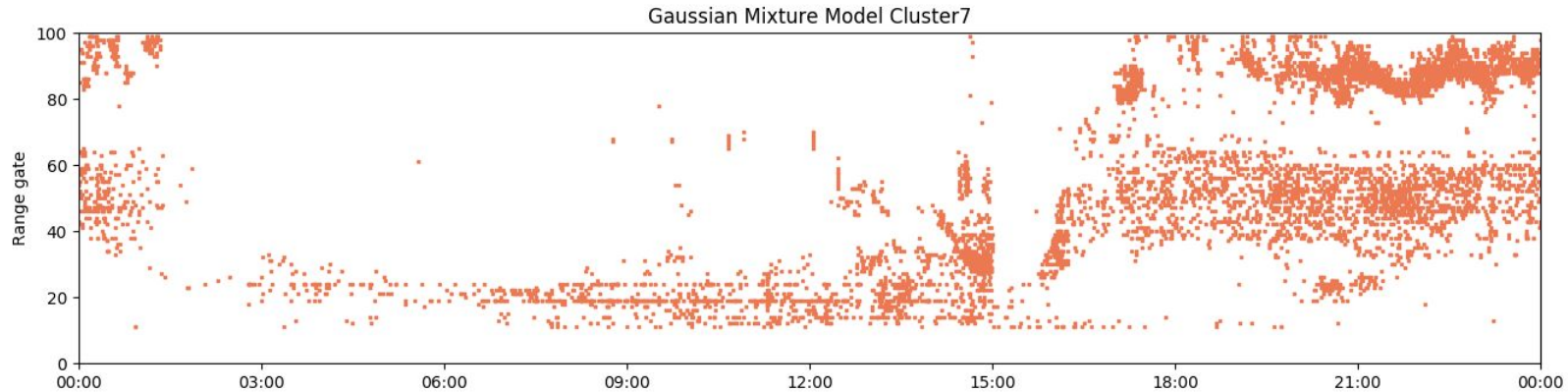


Gaussian Mixture Model Cluster2



# Comparing mid-latitude and high-latitude

CVW 2-7-18

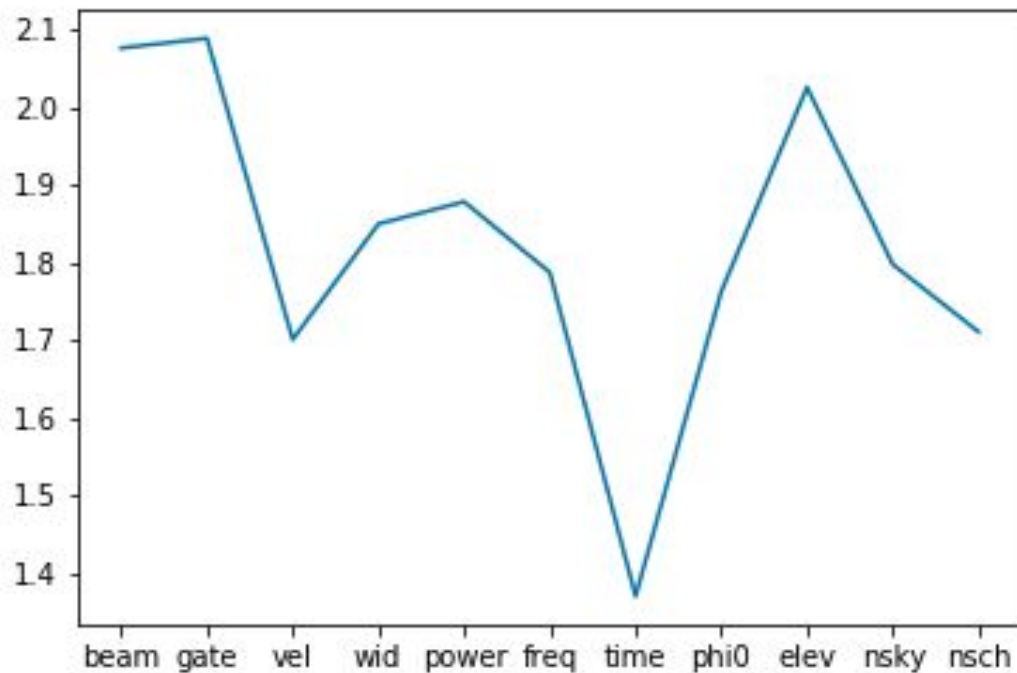


	beam	gate	vel	wid	power	phi0	time
var	36.855498625514166	720.8709707119998	139546.84563549238	5366.414710805141	24.344025027322395	4.170622114823706	0.06321287378376932
med	7.0	53.0	-0.7506966590881348	27.274415969848633	10.879316806793213	-0.3799201250076294	736732.8154141551
mean	10.067556060175987	57.09977292080613	4.997717326808907	43.79629185254508	12.06709424413269	-0.158927113260468	736732.7212298575
max	23.0	99.0	3669.947021484375	798.5252075195312	37.452022552490234	75.33321380615234	736732.9999608797
min	4.0	11.0	-3456.23388671875	-512.9129638671875	6.000430583953857	-12.399154663085938	736732.0001034491

- High-variance data gets grouped into 1 cluster
- Ways to solve:
  - Data transformation
  - Covariance matrix that limits shape of clusters



# Selecting features/clusters (PCA)

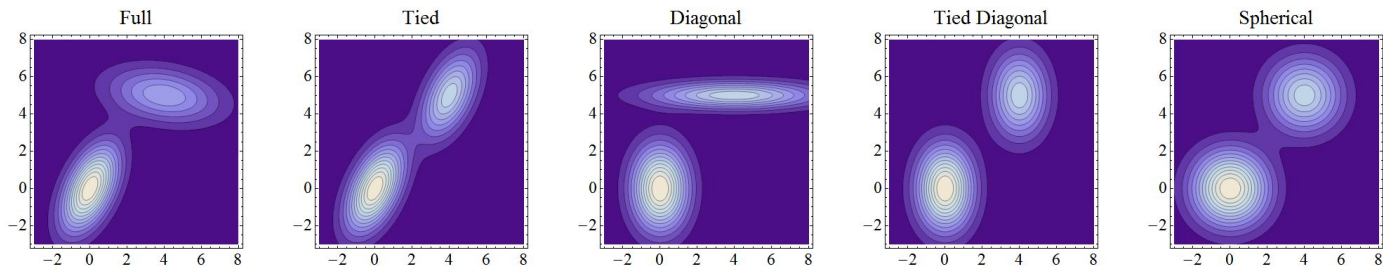


CVW, 2/7/18, all beams

Importance order:

1. Gate
2. Beam
3. Elev
4. Power
5. Width
6. Nsky
7. Freq
8. Phi0
9. Nsch
10. Vel
11. Time

# Covariance matrices



- **Full** means the components may independently adopt any position and shape.
- **Tied** means they have the same shape, but the shape may be anything.
- **Diagonal** means the contour axes are oriented along the coordinate axes, but otherwise the eccentricities may vary between components.
- **Tied Diagonal** is a "tied" situation where the contour axes are oriented along the coordinate axes. (I have added this because initially it was how I misinterpreted "diagonal.")
- **Spherical** is a "diagonal" situation with circular contours (spherical in higher dimensions, whence the name).