

Image Classification

- Why classify?
- Make sense of a landscape
 - Place landscape into categories (classes)
 - Forest, Agriculture, Water, etc
- Classification scheme = structure of classes
 - Depends on needs of users

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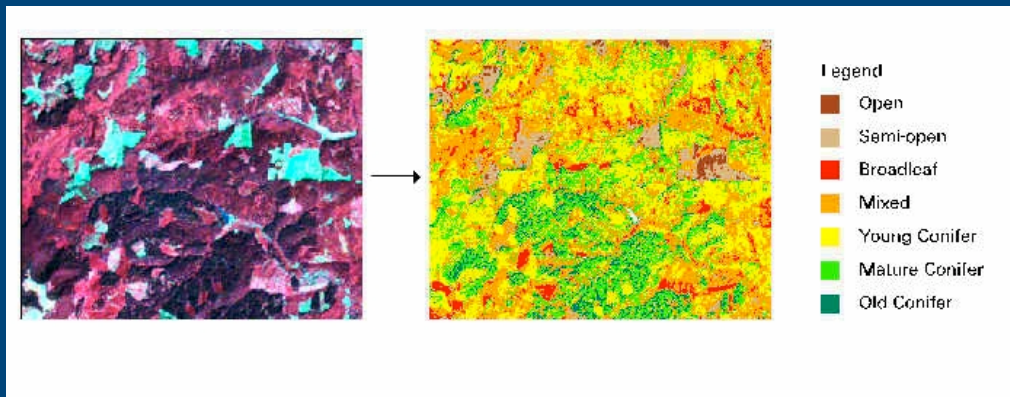
Example Uses

- Provide context
 - Landscape planning or assessment
 - Research projects
- Drive models
 - Global carbon budgets
 - Meteorology
 - Biodiversity

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Example: Near Mary's Peak

- Derived from a 1988 Landsat TM image
- Distinguish types of forest



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Classification

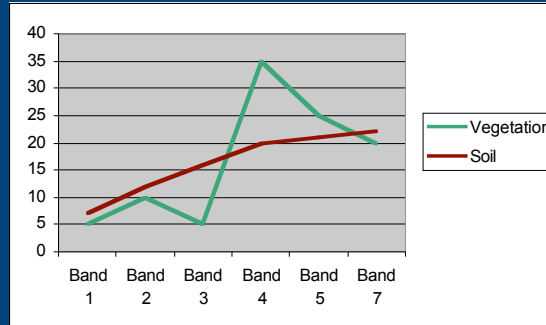
TODAY'S PLAN

- Basic strategy for classifying remotely-sensed images using spectral information
- Supervised Classification
- Unsupervised Classification

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Basic Strategy: How do you do it?

- Use radiometric properties of remote sensor
- Different objects have different spectral signatures



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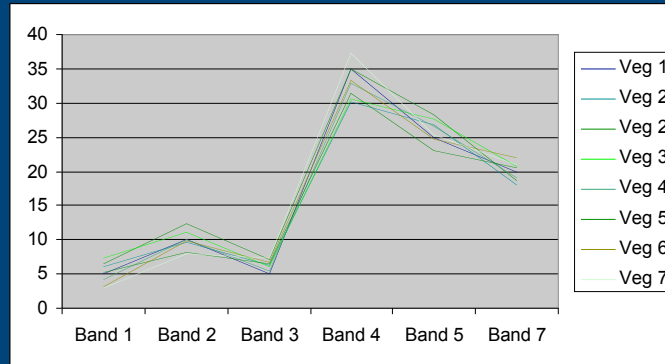
Basic Strategy: How do you do it?

- In an easy world, all “Vegetation” pixels would have exactly the same spectral signature
- Then we could just say that any pixel in an image with that signature was vegetation
- We’d do the same for soil, etc. and end up with a map of classes

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Basic Strategy: How do you do it?

But in reality, that isn't the case. Looking at several pixels with vegetation, you'd see variety in spectral signatures.



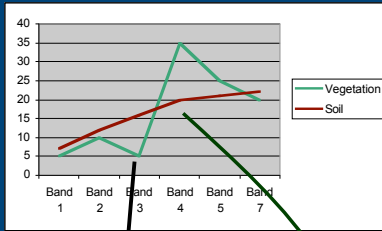
The same would happen for other types of pixels, as well.

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The Classification Trick: Deal with variability

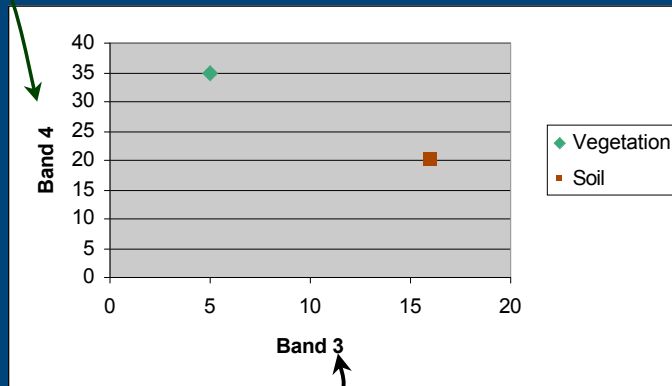
- Different ways of dealing with the variability lead to different ways of classifying images
- To talk about this, we need to look at spectral signatures a little differently

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Think of a pixel's reflectance in 2-dimensional space. The pixel occupies a point in that space.

The vegetation pixel and the soil pixels occupy different points in 2-d space



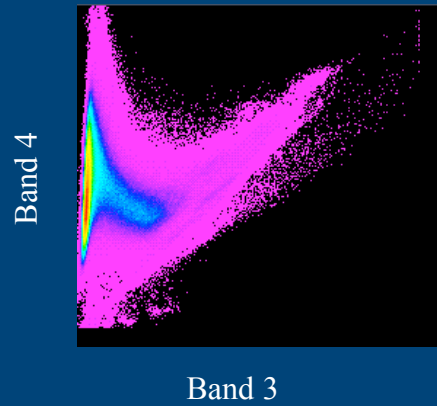
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- In a Landsat scene, instead of two dimensions, we have six spectral dimensions
- Each pixel represents a point in 6-dimensional space
- To be generic to any sensor, we say “**n-dimensional**” space
- For examples that follow, we use 2-d space to illustrate, but principles apply to any n-dimensional space

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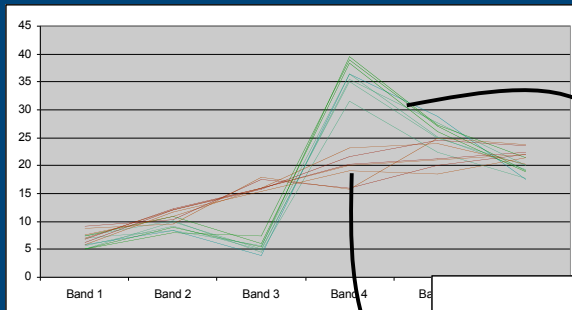
Feature space image

- A graphical representation of the pixels by plotting 2 bands vs. each other
- For a 6-band Landsat image, there are 15 feature space images



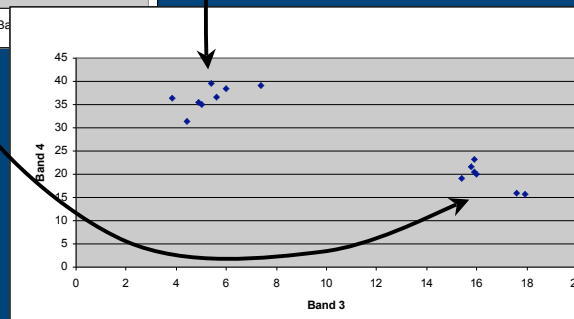
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Basic Strategy: Dealing with variability



With variability, the vegetation pixels now occupy a region, not a point, of n-dimensional space

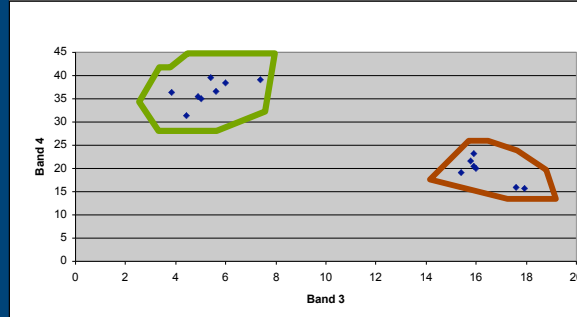
Soil pixels occupy a different region of n-dimensional space



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Basic strategy: Dealing with variability

- Classification:
 - Delineate boundaries of classes in n-dimensional space
 - Assign class names to pixels using those boundaries



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Classification Strategies

- Two basic strategies
 - Supervised classification
 - We impose our perceptions on the spectral data
 - Unsupervised classification
 - Spectral data imposes constraints on our interpretation

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Supervised Classification

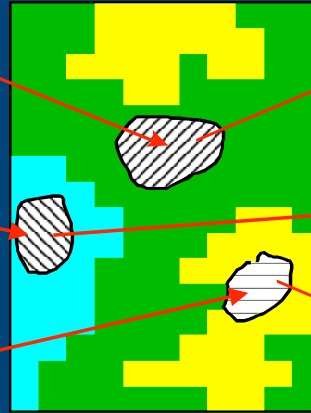
Supervised classification requires the analyst to select training areas where he/she knows what is on the ground and then digitize a polygon within that area...

The computer then creates...

Known Conifer Area

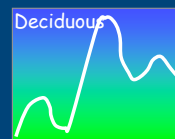
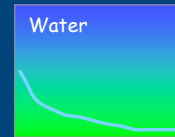
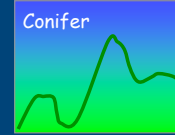
Known Water Area

Known Deciduous Area



Digital Image

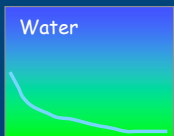
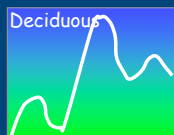
Mean Spectral Signatures



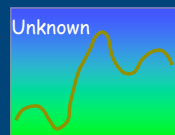
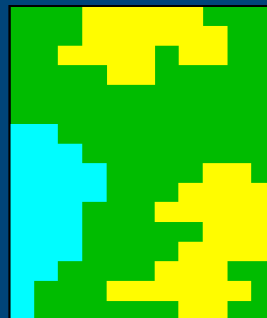
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Supervised Classification

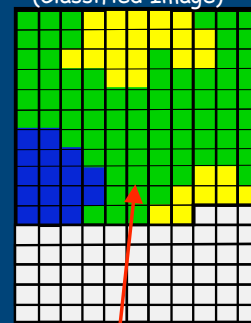
Mean Spectral Signatures



Multispectral Image



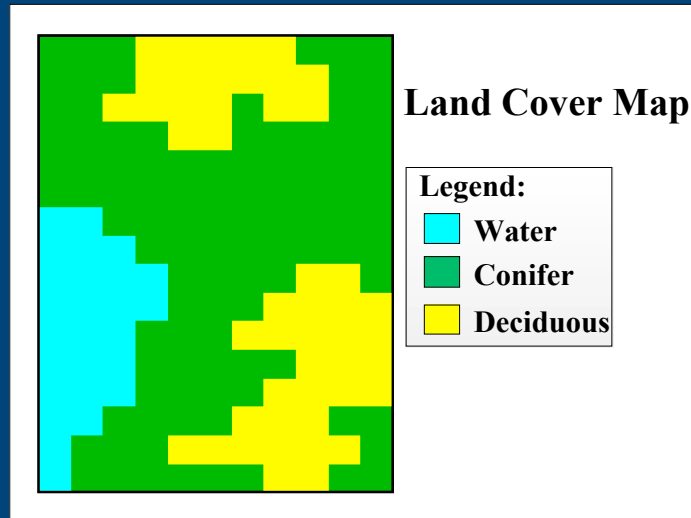
Information (Classified Image)



Spectral Signature of Next Pixel to be Classified

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The Result is Information--in this case a Land Cover map...



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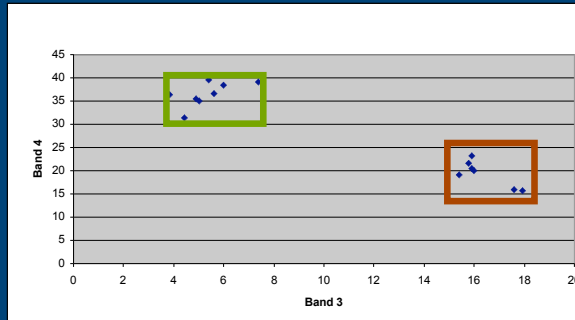
Supervised Classification

- Common Classifiers:
 - Parallelepiped
 - Minimum distance to mean
 - Maximum likelihood

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Supervised Classification

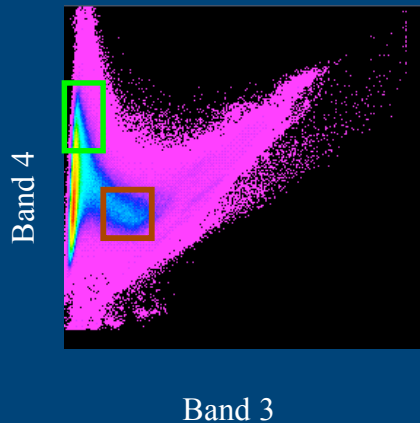
- Parallelepiped Approach
- Pros:
 - Simple
 - Makes few assumptions about character of the classes



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Supervised Classification

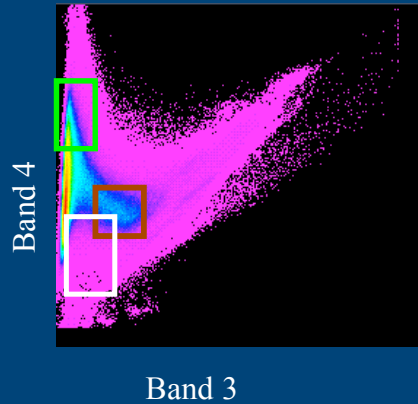
Cons: When we look at all the pixels in image, we find that they cover a continuous region in n-dimensional space: the parallelepiped approach may not be able to classify those regions



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Supervised Classification

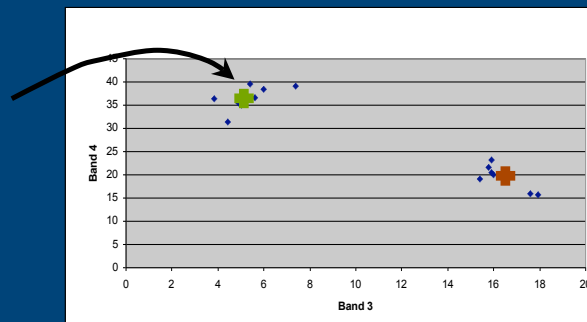
Cons: Parallelepipeds are rectangular, but spectral space is “diagonal,” so classes may overlap



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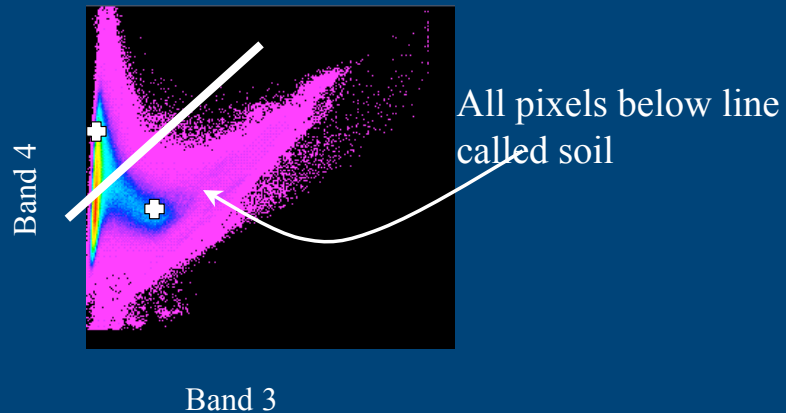
Supervised Classification: Statistical Approaches

- Minimum distance to mean
 - Find mean value of pixels of training sets in n-dimensional space
 - All pixels in image classified according to the class mean to which they are closest



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Supervised Classification: Minimum Distance



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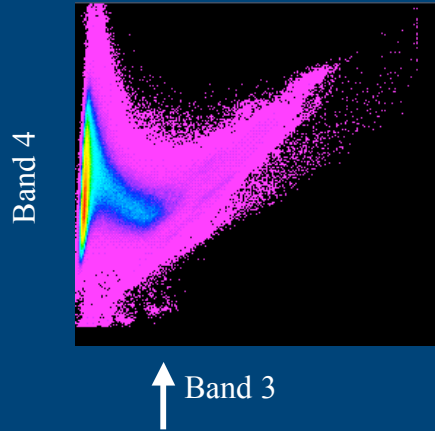
Supervised Classification: Minimum Distance

- Minimum distance
 - Pros:
 - All regions of n-dimensional space are classified
 - Allows for diagonal boundaries (and hence no overlap of classes)

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Supervised Classification

- Minimum distance
 - Con:
 - Assumes that spectral variability is same in all directions, which is not the case



For most pixels, Band 4 is much more variable than Band 3

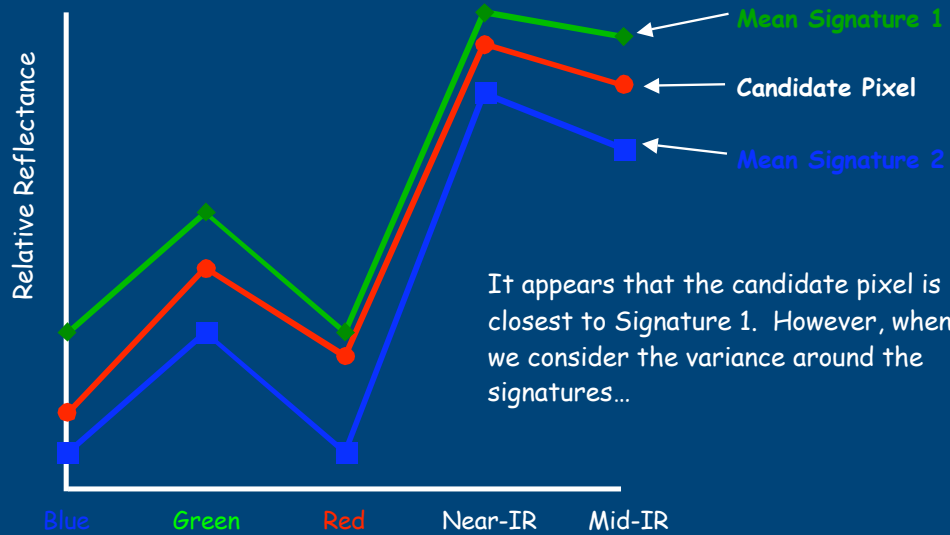
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Supervised Classification: Maximum Likelihood

- Maximum likelihood classification: another statistical approach
- Assume multivariate normal distributions of pixels within classes
- For each class, build a discriminant function
 - For each pixel in the image, this function calculates the probability that the pixel is a member of that class
 - Takes into account mean *and* covariance of training set
- Each pixel is assigned to the class for which it has the highest probability of membership

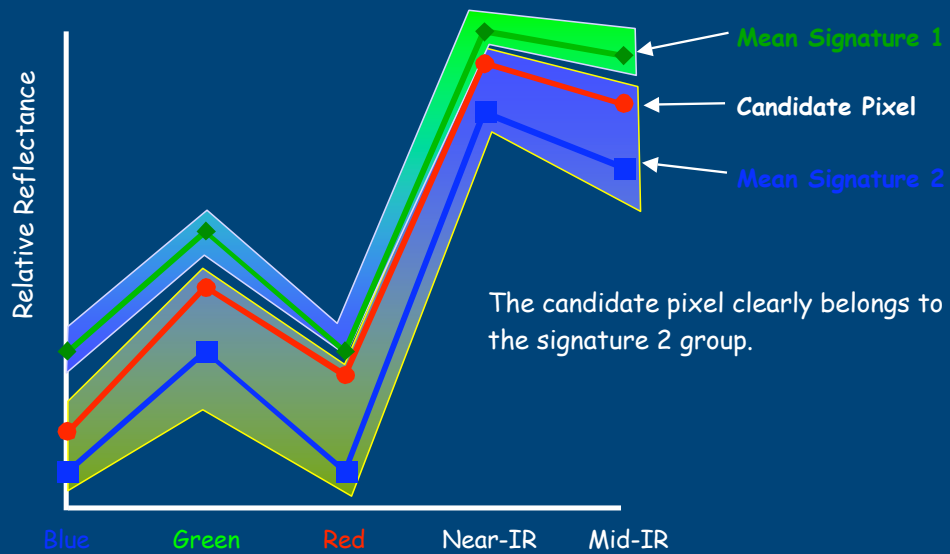
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Maximum Likelihood Classifier



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Maximum Likelihood Classifier



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Supervised Classification

- Maximum likelihood
 - Pro:
 - Most sophisticated; achieves good separation of classes
 - Con:
 - Requires strong training set to accurately describe mean and covariance structure of classes

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Supervised Classification

- In addition to classified image, you can construct a “distance” image
 - For each pixel, calculate the distance between its position in n-dimensional space and the center of class in which it is placed
 - Regions poorly represented in the training dataset will likely be relatively far from class center points
 - May give an indication of how well your training set samples the landscape

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Supervised Classification

- Some advanced techniques
 - Neural networks
 - Use flexible, not-necessarily-linear functions to partition spectral space
 - Contextual classifiers
 - Incorporate spatial or temporal conditions
 - Linear regression
 - Instead of discrete classes, apply proportional values of classes to each pixel; ie. 30% forest + 70% grass

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Classification: Summary

- Use spectral (radiometric) differences to distinguish objects
- Land cover not necessarily equivalent to land use
- Supervised classification
 - Training areas characterize spectral properties of classes
 - Assign other pixels to classes by matching with spectral properties of training sets
- Unsupervised classification
 - Maximize separability of clusters
 - Assign class names to clusters after classification

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