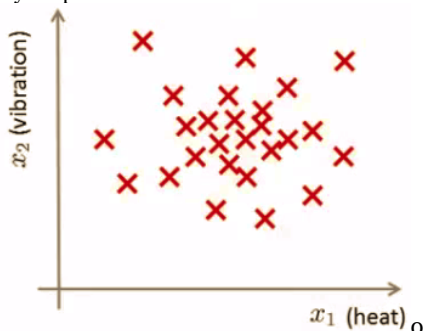


15: Anomaly Detection

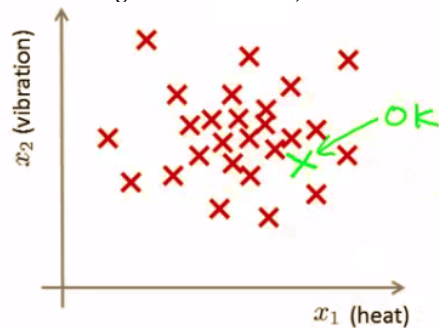
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Anomaly detection - problem motivation

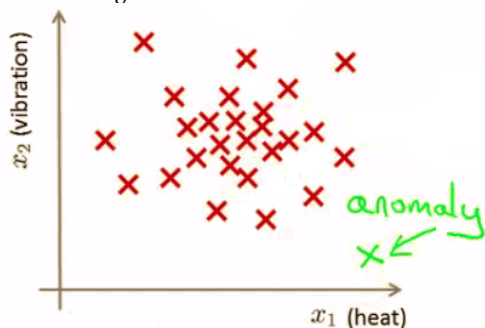
- Anomaly detection is a reasonably commonly used type of machine learning application
 - Can be thought of as a solution to an unsupervised learning problem
 - But, has aspects of supervised learning
- What is anomaly detection?
 - Imagine you're an aircraft engine manufacturer
 - As engines roll off your assembly line you're doing QA
 - Measure some features from engines (e.g. heat generated and vibration)
 - You now have a dataset of x^1 to x^m (i.e. m engines were tested)
 - Say we plot that dataset



- Next day you have a new engine
 - An anomaly detection method is used to see if the new engine is anomalous (when compared to the previous engines)
- If the new engine looks like this;

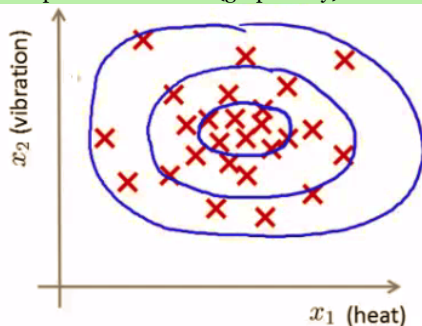


- Probably OK - looks like the ones we've seen before
- But if the engine looks like this



- Uh oh! - this looks like an **anomalous data-point**
- More formally
 - We have a dataset which contains **normal** (data)
 - How we ensure they're normal is up to us
 - In reality it's OK if there are a few which aren't actually normal
 - Using that dataset as a reference point we can see if other examples are **anomalous**
- How do we do this?
 - First, using our training dataset we build a model

- We can access this model using $p(x)$
 - This asks, "What is the probability that example x is normal"
- Having built a model
 - if $p(x_{\text{test}}) < \epsilon \rightarrow$ flag this as an anomaly
 - if $p(x_{\text{test}}) \geq \epsilon \rightarrow$ this is OK
 - ϵ is some threshold probability value which we define, depending on how sure we need/want to be
- We expect our model to (graphically) look something like this;




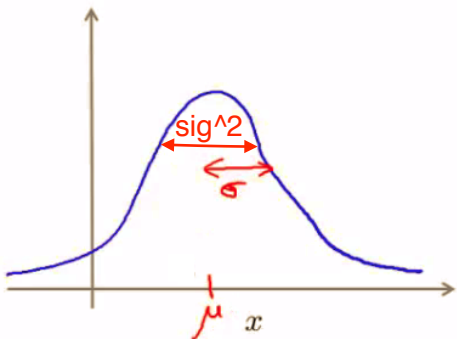
- i.e. this would be our model if we had 2D data

Applications

- Fraud detection
 - Users have activity associated with them, such as
 - Length on time on-line
 - Location of login
 - Spending frequency
 - Using this data we can build a model of what normal users' activity is like
 - What is the probability of "normal" behavior?
 - Identify unusual users by sending their data through the model
 - Flag up anything that looks a bit weird
 - Automatically block cards/transactions
- Manufacturing
 - Already spoke about aircraft engine example
- Monitoring computers in data center
 - If you have many machines in a cluster
 - Computer features of machine
 - x_1 = memory use
 - x_2 = number of disk accesses/sec
 - x_3 = CPU load
 - In addition to the measurable features you can also define your own complex features
 - x_4 = CPU load/network traffic
 - If you see an anomalous machine
 - Maybe about to fail
 - Look at replacing bits from it

The Gaussian distribution (optional)

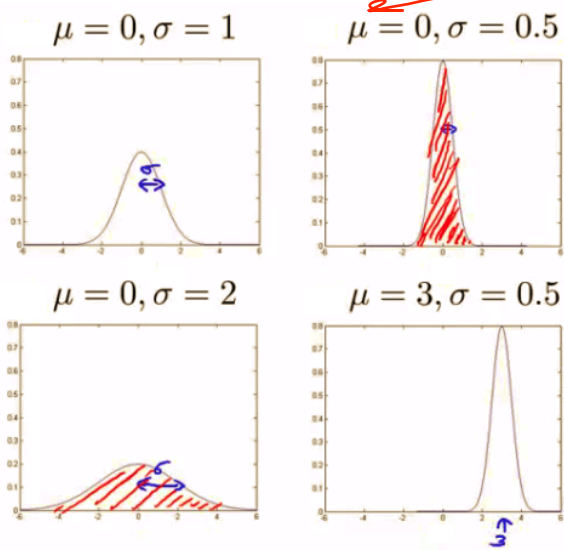
- Also called the **normal distribution**
- Example
 - Say x (data set) is made up of real numbers
 - Mean is μ
 - Variance is σ^2
 - σ is also called the **standard deviation** - specifies the width of the Gaussian probability
 - The data has a Gaussian distribution
 - Then we can write this $\sim N(\mu, \sigma^2)$
 - \sim means = is distributed as
 - N (should really be "script" N (even curlier!) \rightarrow means normal distribution) the N should look like this 
 - μ, σ^2 represent the mean and variance, respectively
 - These are the two parameters a Gaussian means
 - Looks like this;



- This specifies the probability of x taking a value
 - As you move away from μ
- Gaussian equation is
 - $P(x : \mu, \sigma^2)$ (probability of x, parameterized by the mean and squared variance)

$$= \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

- Some examples of Gaussians below
 - Area is always the same (must = 1)
 - But width changes as standard deviation changes

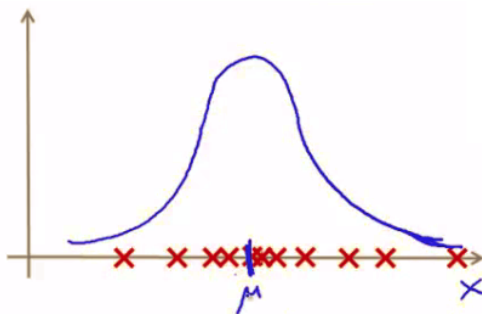


Parameter estimation problem

- What is it?
 - Say we have a data set of m examples
 - Give each example is a real number - we can plot the data on the x axis as shown below



- Problem is - say you suspect these examples come from a Gaussian
 - Given the dataset can you estimate the distribution?
- Could be something like this



- Seems like a reasonable fit - data seems like a higher probability of being in the central region, lower probability of being further away
 - Estimating μ and σ^2
 - μ = average of examples
 - σ^2 = standard deviation squared
- $$\sigma^2 = \frac{1}{M} \sum_{i=1}^M (x^{(i)} - \mu)^2$$
- where M = total number of samples
- As a side comment
 - These parameters are the maximum likelihood estimation values for μ and σ^2
 - You can also do $1/(m)$ or $1/(m-1)$ doesn't make too much difference

- Slightly different mathematical problems, but in practice it makes little difference

Anomaly detection algorithm

- Unlabeled training set of m examples
 - Data = $\{x^1, x^2, \dots, x^m\}$
 - Each example is an n-dimensional vector (i.e. a feature vector)
 - We have n features!
 - Model $P(x)$ from the data set
 - What are high probability features and low probability features
 - x is a vector
 - So model $p(x)$ as
 - $= p(x_1; \mu_1, \sigma_1^2) * p(x_2; \mu_2, \sigma_2^2) * \dots * p(x_n; \mu_n, \sigma_n^2)$

prob. of x_1 (as parameterized by μ_1 and σ_1^2) AND
prob. of x_2 (as parameterized by μ_2 and σ_2^2) AND ...
 - Multiply the probability of each features by each feature
 - We model each of the features by assuming each feature is distributed according to a Gaussian distribution
 - $p(x_i; \mu_i, \sigma_i^2)$

not necessarily the same gaussian (hence the different params.)
 - The probability of feature x_i given μ_i and σ_i^2 , using a Gaussian distribution
 - As a side comment
 - Turns out this equation makes an independence assumption for the features, although algorithm works if features are independent or not
 - Don't worry too much about this, although if you're features are tightly linked you should be able to do some dimensionality reduction anyway!
 - We can write this chain of multiplication more compactly as follows;

$$= \prod_{j=1}^n p(x_j; \mu_j, \sigma_j^2)$$

 - Capital Π (II) is the product of a set of values
- The problem of estimation this distribution is sometimes call the problem of density estimation

Algorithm

1. Choose features x_i that you think might be indicative of anomalous examples.

2. Fit parameters $\mu_1, \dots, \mu_n, \sigma_1^2, \dots, \sigma_n^2$

$$\mu_j = \frac{1}{m} \sum_{i=1}^m x_j^{(i)} \quad \text{mean of feature } j \text{ over all samples}$$

$$\sigma_j^2 = \frac{1}{m} \sum_{i=1}^m (x_j^{(i)} - \mu_j)^2 \quad \text{std. deviation (sqr) of feature } j \text{ over all samples}$$

3. Given new example x , compute $p(x)$:

$$p(x) = \prod_{j=1}^n p(x_j; \mu_j, \sigma_j^2) = \prod_{j=1}^n \frac{1}{\sqrt{2\pi}\sigma_j} \exp\left(-\frac{(x_j - \mu_j)^2}{2\sigma_j^2}\right)$$

Anomaly if $p(x) < \varepsilon$

• **1 - Chose features**

- Try to come up with features which might help identify something anomalous - may be unusually large or small values
- More generally, chose features which describe the general properties
- This is nothing unique to anomaly detection - it's just the idea of building a sensible feature vector

• **2 - Fit parameters**

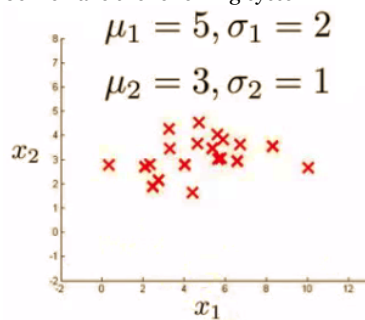
- Determine parameters for each of your examples μ_i and σ_i^2
 - Fit is a bit misleading, really should just be "Calculate parameters for 1 to n"
- So you're calculating standard deviation and mean for each feature
- You should of course use some vectorized implementation rather than a loop probably

• **3 - compute p(x)**

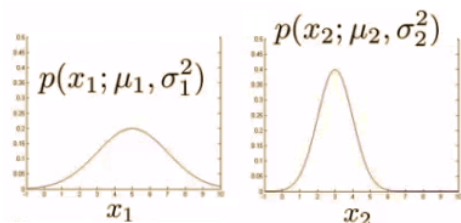
- You compute the formula shown (i.e. the formula for the Gaussian probability)
- If the number is very small, very low chance of it being "normal" means that @ least one of the features is unlikely (is either far left or right of that features gaussian distribution)

Anomaly detection example

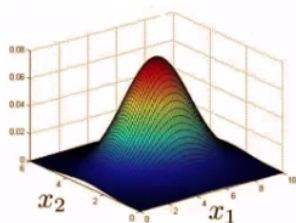
- x_1
 - Mean is about 5
 - Standard deviation looks to be about 2
- x_2
 - Mean is about 3
 - Standard deviation about 1
- So we have the following system



- If we plot the Gaussian for x_1 and x_2 we get something like this



- If you plot the product of these things you get a surface plot like this



- With this surface plot, the height of the surface is the probability - $p(x)$
- We can't always do surface plots, but for this example it's quite a nice way to show the probability of a 2D feature vector
- Check if a value is anomalous
 - Set epsilon as some value
 - Say we have two new data points new data-point has the values
 - x^1_{test}
 - x^2_{test}
 - We compute
 - $p(x^1_{\text{test}}) = 0.436 \geq \text{epsilon}$ (~40% chance it's normal)
 - Normal
 - $p(x^2_{\text{test}}) = 0.0021 < \text{epsilon}$ (~0.2% chance it's normal)
 - Anomalous
 - What this is saying is if you look at the surface plot, all values above a certain height are normal, all the values below that threshold are probably anomalous

Developing and evaluating an anomaly detection system

- Here talk about developing a system for anomaly detection
 - How to evaluate an algorithm
- Previously we spoke about the importance of real-number evaluation
 - Often need to make a lot of choices (e.g. features to use)
 - Easier to evaluate your algorithm if it returns a **single number** to show if changes you made improved or worsened an algorithm's performance
 - To develop an anomaly detection system quickly, would be helpful to have a way to evaluate your algorithm
- Assume we have some labeled data
 - So far we've been treating anomalous detection with unlabeled data
 - If you have labeled data allows evaluation
 - i.e. if you think something is anomalous you can be sure if it is or not
- So, taking our engine example
 - You have some labeled data
 - Data for engines which were non-anomalous $\rightarrow y = 0$
 - Data for engines which were anomalous $\rightarrow y = 1$
 - Training set is the collection of normal examples
 - OK even if we have a few anomalous data examples
 - Next define
 - Cross validation set
 - Test set
 - For both assume you can include a few examples which have anomalous examples
 - Specific example
 - Engines
 - Have 10 000 good engines
 - OK even if a few bad ones are here...
 - LOTS of $y = 0$
 - 20 flawed engines
 - Typically when $y = 1$ have 2-50
 - Split into
 - Training set: 6000 good engines ($y = 0$)
 - CV set: 2000 good engines, 10 anomalous
 - Test set: 2000 good engines, 10 anomalous
 - Ratio is 3:1:1
 - Sometimes we see a different way of splitting
 - Take 6000 good in training
 - Same CV and test set (4000 good in each) different 10 anomalous,
 - Or even 20 anomalous (same ones)
 - This is bad practice - should use different data in CV and test set
 - Algorithm evaluation
 - Take trainings set $\{x^1, x^2, \dots, x^m\}$
 - Fit model $p(x)$
 - On cross validation and test set, test the example x
 - $y = 1$ if $p(x) < \text{epsilon}$ (anomalous)

- $y = 0$ if $p(x) \geq \epsilon$ (normal)
 - Think of algorithm as trying to predict if something is anomalous
 - But you have a label so can check!
 - Makes it look like a supervised learning algorithm
- What's a good metric to use for evaluation
 - $y = 0$ is very common
 - So classification would be bad
 - Compute fraction of true positives/false positive/false negative/true negative
 - Compute precision/recall
 - Compute **F1-score**
- Earlier, also had **epsilon** (the threshold value)
 - Threshold to show when something is anomalous
 - If you have CV set you can see how varying epsilon effects various evaluation metrics
 - Then pick the value of epsilon which maximizes the score on your CV set
 - Evaluate algorithm using cross validation
 - Do final algorithm evaluation on the test set

Anomaly detection vs. supervised learning

- If we have labeled data, we not use a supervised learning algorithm?
 - Here we'll try and understand when you should use supervised learning and when anomaly detection would be better

Anomaly detection

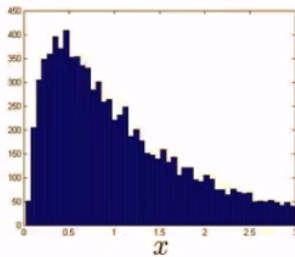
- **Very small number of positive examples**
 - Save positive examples just for CV and test set
 - Consider using an anomaly detection algorithm
 - Not enough data to "learn" positive examples
- **Have a very large number of negative examples** have a lot of what we don't want
 - Use these negative examples for $p(x)$ fitting
 - Only need negative examples for this
- **Many "types" of anomalies**
 - Hard for an algorithm to learn from positive examples when anomalies may look nothing like one another
 - So anomaly detection doesn't know what they look like, but knows what they *don't* look like
 - When we looked at SPAM email,
 - Many types of SPAM
 - For the spam problem, usually enough positive examples
 - So this is why we usually think of SPAM as supervised learning
- Application and why they're anomaly detection
 - **Fraud detection**
 - Many ways you may do fraud
 - If you're a major on line retailer/very subject to attacks, sometimes might shift to supervised learning
 - **Manufacturing**
 - If you make HUGE volumes maybe have enough positive data -> make supervised
 - Means you make an assumption about the kinds of errors you're going to see
 - It's the unknown unknowns we don't like!
 - **Monitoring machines in data**

Supervised learning

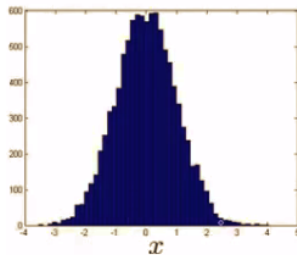
- **Reasonably large number of positive and negative examples**
- Have enough positive examples to give your algorithm the opportunity to see what they look like
 - If you expect anomalies to look anomalous in the same way
- Application
 - Email/SPAM classification
 - Weather prediction
 - Cancer classification

Choosing features to use

- One of the things which has a huge effect is which features are used
- **Non-Gaussian features**
 - Plot a histogram of data to check it has a Gaussian description - nice sanity check
 - Often still works if data is non-Gaussian
 - Use **hist** command to plot histogram
 - Non-Gaussian data might look like this



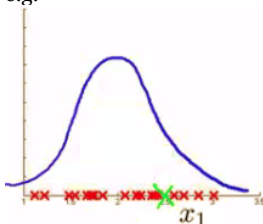
- Can play with different transformations of the data to make it look more Gaussian
- Might take a log transformation of the data
 - i.e. if you have some feature x_1 , replace it with $\log(x_1)$



- This looks much more Gaussian
- Or do $\log(x_1+c)$
 - Play with c to make it look as Gaussian as possible
- Or do $x^{1/2}$
- Or do $x^{1/3}$

Error analysis for anomaly detection

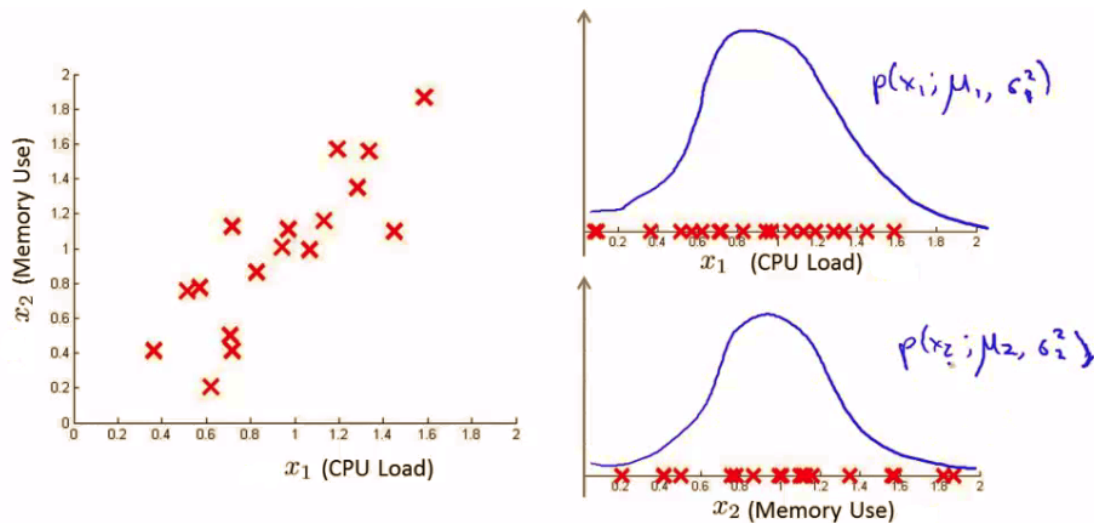
- Good way of coming up with features
- Like supervised learning error analysis procedure
 - Run algorithm on CV set
 - See which one it got wrong
 - Develop new features based on trying to understand *why* the algorithm got those examples wrong
- Example
 - $p(x)$ large for normal, $p(x)$ small for abnormal
 - e.g.



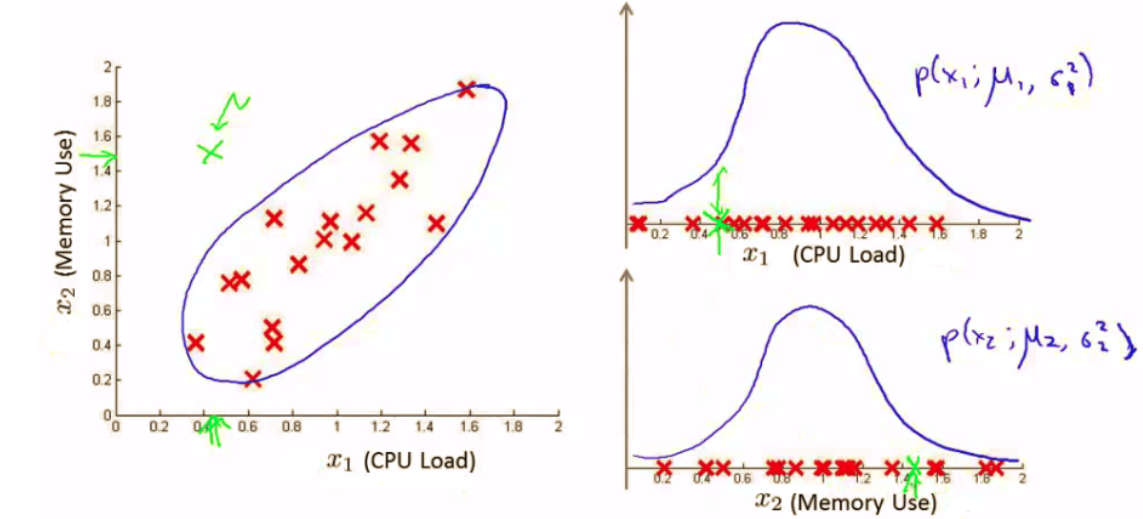
- Here we have one dimension, and our anomalous value is sort of buried in it (in green - Gaussian superimposed in blue)
 - Look at data - see what went wrong
 - Can looking at that example help develop a new feature (x_2) which can help distinguish further anomalous
- Example - data center monitoring
 - Features
 - x_1 = memory use
 - x_2 = number of disk access/sec
 - x_3 = CPU load
 - x_4 = network traffic
 - We suspect CPU load and network traffic grow linearly with one another
 - If server is serving many users, CPU is high and network is high
 - Fail case is infinite loop, so CPU load grows but network traffic is low
 - New feature - CPU load/network traffic
 - May need to do feature scaling

Multivariate Gaussian distribution

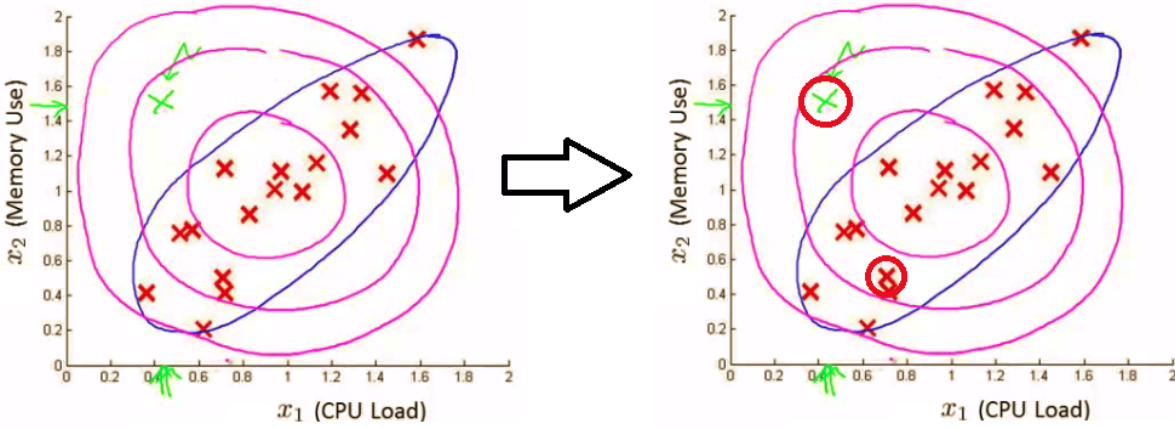
- Is a slightly different technique which can sometimes catch some anomalies which non-multivariate Gaussian distribution anomaly detection fails to
 - Unlabeled data looks like this



- Say you can fit a Gaussian distribution to CPU load and memory use
- Lets say in the test set we have an example which looks like an anomaly (e.g. $x_1 = 0.4, x_2 = 1.5$)
 - Looks like most of data lies in a region far away from this example
 - Here memory use is high and CPU load is low (if we plot x_1 vs. x_2 our green example looks miles away from the others)
- Problem is, if we look at each feature individually they may fall within acceptable limits - the issue is we know we shouldn't don't get those kinds of values **together**
 - But individually, they're both acceptable



- This is because our function makes probability prediction in concentric circles around the the means of both



- Probability of the two red circled examples is basically the same, even though we can clearly see the green one as an outlier
 - Doesn't understand the meaning

Multivariate Gaussian distribution model

- To get around this we develop the **multivariate Gaussian distribution**
 - Model $p(x)$ all in one go, instead of each feature separately
 - What are the parameters for this new model?
 - μ - which is an n dimensional vector (where n is number of features)
 - Σ - which is an $[n \times n]$ matrix - the **covariance matrix**
- For the sake of completeness, the formula for the multivariate Gaussian distribution is as follows

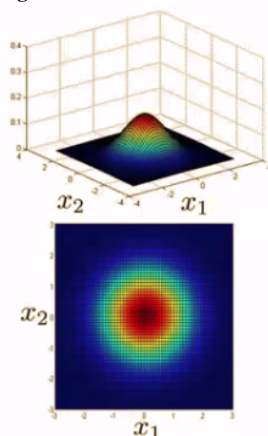
$$p(x; \mu, \Sigma) = \frac{1}{(2\pi)^{n/2} |\Sigma|^{1/2}} \exp\left(-\frac{1}{2} (x-\mu)^T \Sigma^{-1} (x-\mu)\right)$$

- NB don't memorize this - you can always look it up
- What does this mean?
 - $|\Sigma|$ = absolute value of Σ (determinant of sigma)
 - This is a mathematic function of a matrix
 - You can compute it in MATLAB using `det(sigma)`
- More importantly, what does this $p(x)$ look like?

◦ 2D example

$$\mu = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad \Sigma = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

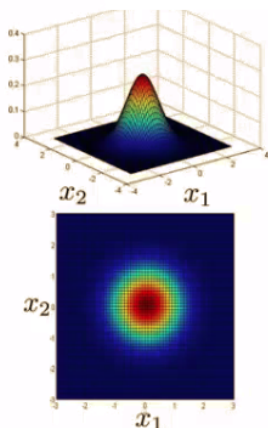
- Sigma is sometimes call the identity matrix



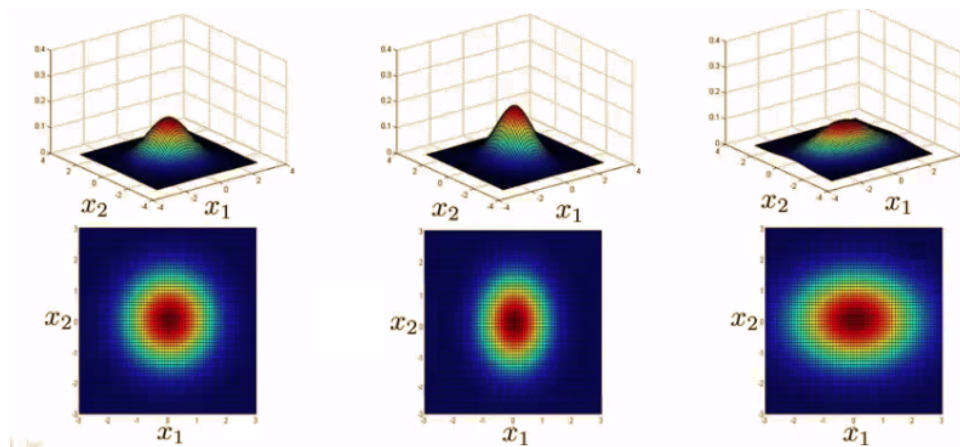
- $p(x)$ looks like this
 - For inputs of x_1 and x_2 the height of the surface gives the value of $p(x)$
- What happens if we change Sigma?

$$\mu = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad \Sigma = \begin{bmatrix} 0.6 & 0 \\ 0 & 0.6 \end{bmatrix}$$

◦ So now we change the plot to



- Now the width of the bump decreases and the height increases
- If we set sigma to be different values this changes the identity matrix and we change the shape of our graph

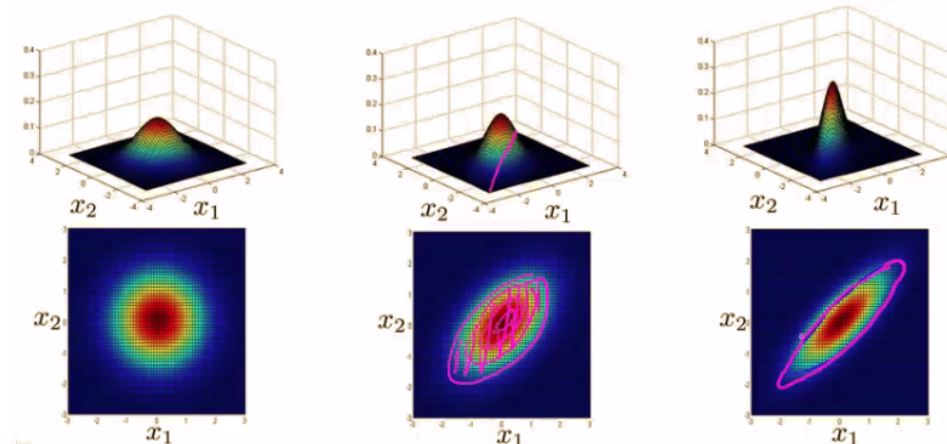


- Using these values we can, therefore, define the shape of this to better fit the data, rather than assuming symmetry in every dimension
- One of the cool things is you can use it to model correlation between data
 - If you start to change the off-diagonal values in the covariance matrix you can control how well the various dimensions correlation

$$\mu = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Sigma = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\mu = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Sigma = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}$$

$$\mu = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Sigma = \begin{bmatrix} 1 & 0.8 \\ 0.8 & 1 \end{bmatrix}$$



- So we see here the final example gives a very tall thin distribution, shows a strong positive correlation
- We can also make the off-diagonal values negative to show a negative correlation
- Hopefully this shows an example of the kinds of distribution you can get by varying sigma
 - We can, of course, also move the mean (μ) which varies the peak of the distribution

Applying multivariate Gaussian distribution to anomaly detection

- Saw some examples of the kinds of distributions you can model
 - Now let's take those ideas and look at applying them to different anomaly detection algorithms
- As mentioned, multivariate Gaussian modeling uses the following equation;

$$p(x; \mu, \Sigma) = \frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma|^{\frac{1}{2}}} \exp \left(-\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu) \right)$$

- Which comes with the parameters μ and Σ
 - Where
 - μ - the mean (n-dimensional vector)
 - Σ - covariance matrix ([n x n] matrix)
- Parameter fitting/estimation problem
 - If you have a set of examples
 - $\{x^1, x^2, \dots, x^m\}$
 - The formula for estimating the parameters is

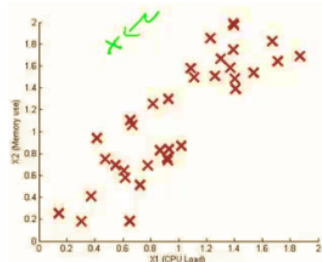
$$\mu = \frac{1}{m} \sum_{i=1}^m x^{(i)}$$

$$\Sigma = \frac{1}{m} \sum_{i=1}^m (x^{(i)} - \mu)(x^{(i)} - \mu)^T$$

- Using these two formulas you get the parameters

Anomaly detection algorithm with multivariate Gaussian distribution

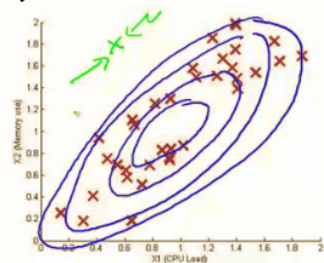
- 1) Fit model - take data set and calculate μ and Σ using the formula above
- 2) We're next given a new example (x_{test}) - see below



- For it compute $p(x)$ using the following formula for multivariate distribution

$$p(x) = \frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma|^{\frac{1}{2}}} \exp \left(-\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu) \right)$$

- 3) Compare the value with ϵ (threshold probability value)
 - if $p(x_{\text{test}}) < \epsilon$ --> flag this as an anomaly
 - if $p(x_{\text{test}}) \geq \epsilon$ --> this is OK
- If you fit a multivariate Gaussian model to our data we build something like this



- Which means it's likely to identify the green value as anomalous
- Finally, we should mention how multivariate Gaussian relates to our original simple Gaussian model (where each feature is looked at individually)
 - Original model corresponds to multivariate Gaussian where the Gaussians' contours are axis aligned
 - i.e. the normal Gaussian model is a special case of multivariate Gaussian distribution

- This can be shown mathematically
- Has this constraint that the covariance matrix sigma as ZEROS on the non-diagonal values

$$p(x; \mu, \Sigma) = \frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma|^{\frac{1}{2}}} \exp \left(-\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu) \right)$$

where $\Sigma = \begin{bmatrix} \sigma_1^2 & 0 & \dots & 0 \\ 0 & \sigma_2^2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_n^2 \end{bmatrix}$

- If you plug your variance values into the covariance matrix the models are actually identical

Original model vs. Multivariate Gaussian

Original Gaussian model

- Probably used more often
- There is a need to manually create features to capture anomalies where x_1 and x_2 take unusual combinations of values
 - So **need to make extra features**
 - Might not be obvious what they should be
 - This is always a risk - where you're using your own expectation of a problem to "predict" future anomalies
 - Typically, the things that catch you out aren't going to be the things you thought of
 - If you thought of them they'd probably be avoided in the first place
 - Obviously this is a bigger issue, and one which may or may not be relevant depending on your problem space
- Much **cheaper computationally**
- **Scales much better** to very large feature vectors
 - Even if $n = 100\ 000$ the original model works fine
- **Works well even with a small training set**
 - e.g. 50, 100
- Because of these factors it's used more often because it really represents a optimized but axis-symmetric specialization of the general model

Multivariate Gaussian model

- Used less frequently
- **Can capture feature correlation**
 - So no need to create extra values
- **Less computationally efficient**
 - Must compute inverse of matrix which is $[n \times n]$
 - So lots of features is bad - makes this calculation very expensive
 - So if $n = 100\ 000$ not very good
- **Needs for $m > n$**
 - i.e. number of examples must be greater than number of features
 - If this is not true then we have a singular matrix (non-invertible)
 - So should be used only in $m \gg n$
- If you find the matrix is non-invertible, could be for one of two main reasons
 - $m < n$
 - So use original simple model
 - Redundant features (i.e. linearly dependent)
 - i.e. two features that are the same
 - If this is the case you could use PCA or sanity check your data