# Real Bogus & Machine Learning for transient astronomy

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Variability studies in astronomy refer to the fluctuation of brightness over time of an astronomical object.

We use variability studies for several things:

- Object classification
- NEO's studies
- Stellar systems ($\alpha$ Cen)
- Distance measures
- Cosmology and cosmography

There are several types of variability:

- Periodic Variability

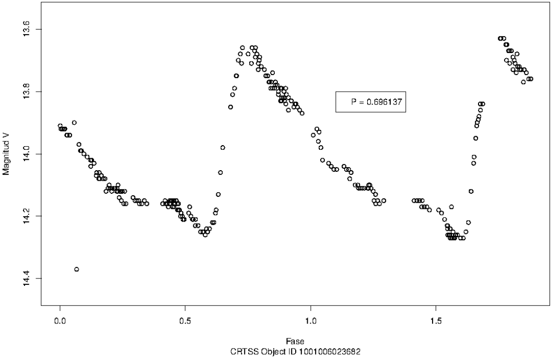


Figura: CRTSS light curve data for a RR Lyra star.

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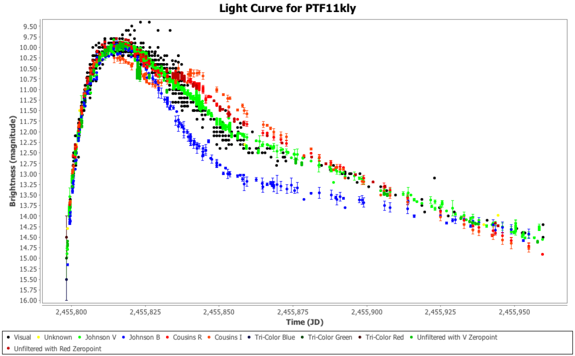


Figura: Supernova Type Ia lightcurve from PTF11kly. (PTF data).

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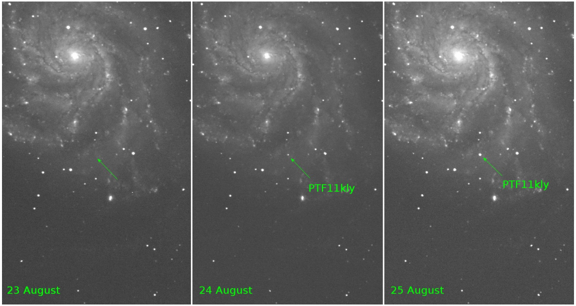


Figura: Supernova Type Ia (PTF11kly).

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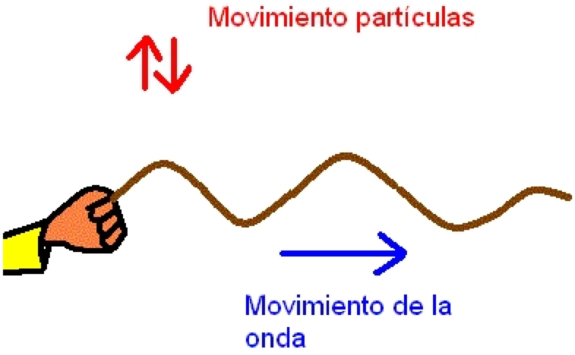

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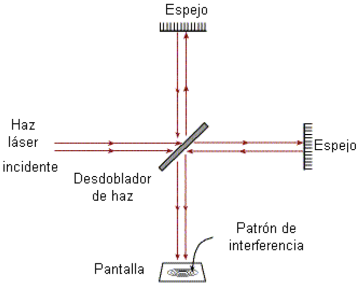
For higher precision and sensibility this instruments need to be Km long



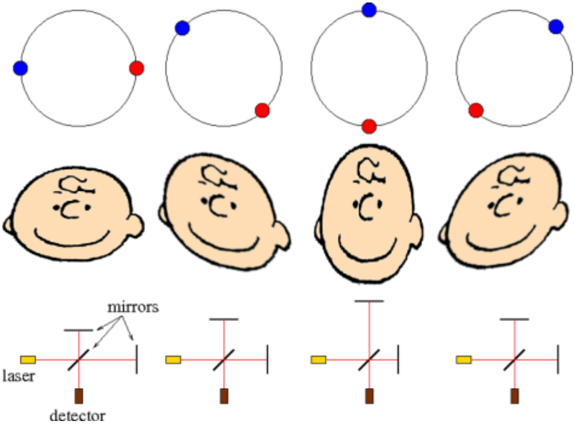




Figura: Perturbations induced by GW (from
http://www.einstein-online.info/spotlights/gravWav).

Localization errors of the candidates depends on N of detectors.

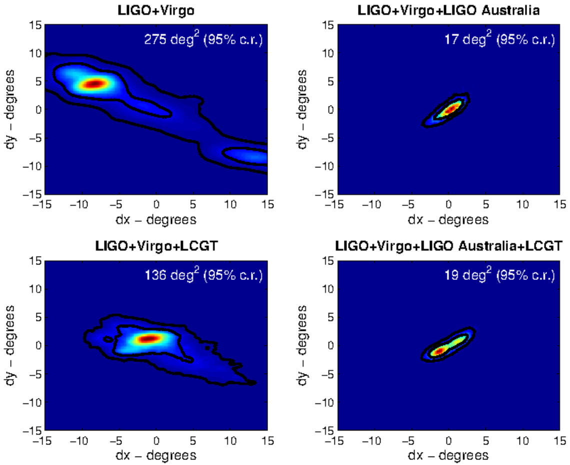



Figura: Sky localization of a low-limit SNR.

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This independent tracer are the **Compact Object Mergers**.
This objects would produce bursts of EM radiation, (the so called "smoking gun").
In the optical range we find the Kilonova event.

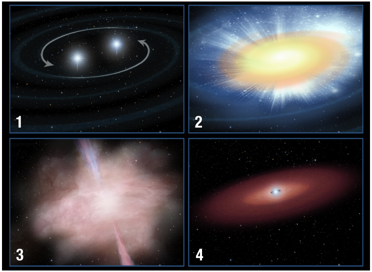


Figura: Compact object merger cartoon

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So... what is needed to catch a Kilonova??

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Project TOROS - TORITOS


# Image analysis

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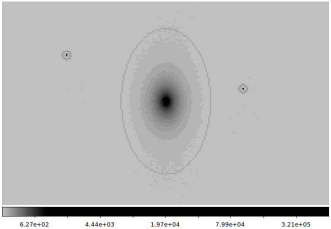
- Aperture photometry
  - Calculates the energy received on a given area of the image
  - $m_1 - m_2 = -2{,}5 log_{10} \left( \frac{E_1}{E_2} \right)$

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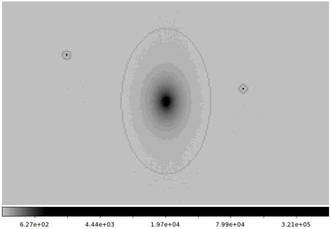


- Difference Image Analysis
  - It is like “fancy substracting” two images

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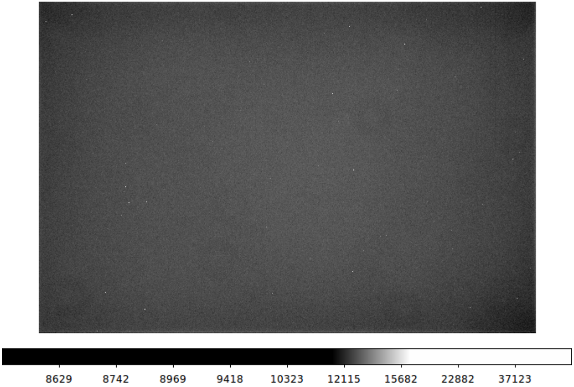
In a perfect substraction we would be having a image like this:



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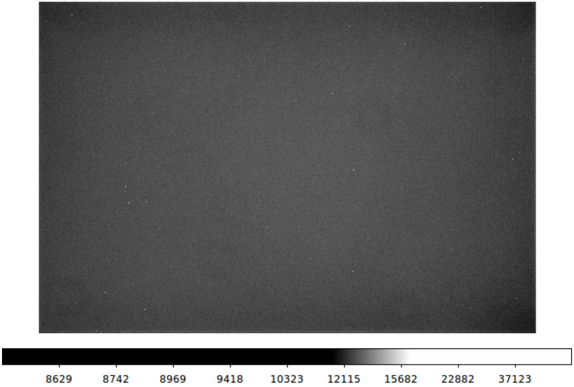
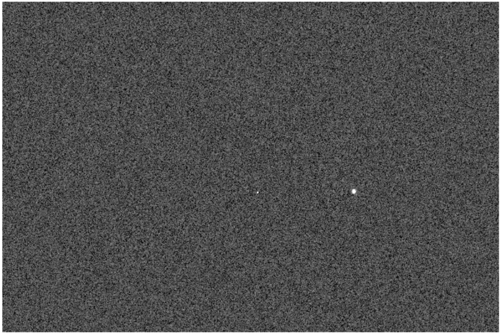



In this example there are not transients. Althoug we can see some random noise resembling stars.

# Image analysis

This image presents transients:



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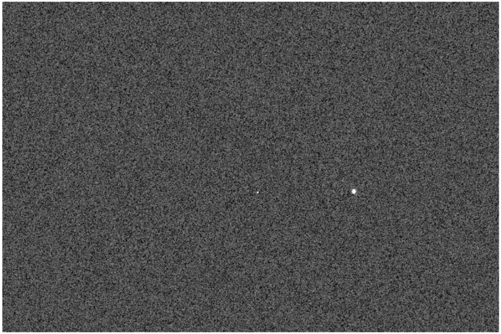
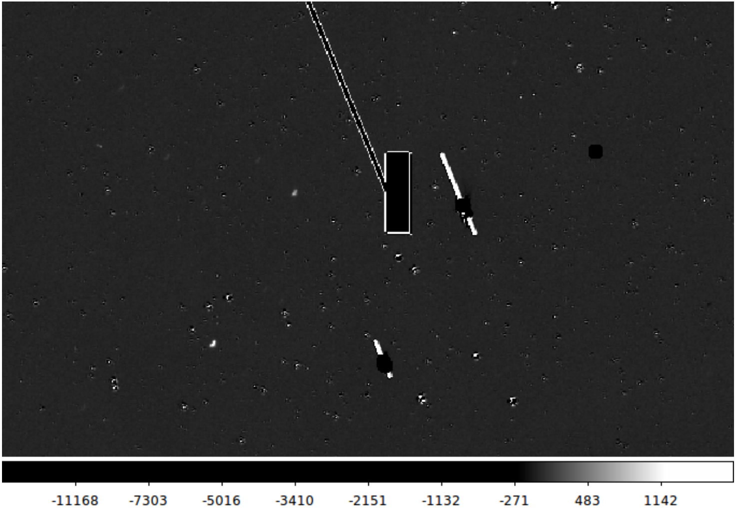


But this two are fake images.

# Image analysis

This is an actual subtraction from real data:



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The classificator that separates false from real candidates is called Real-Bogus

# Statistical Learning

First of all: *What is machine learning?*

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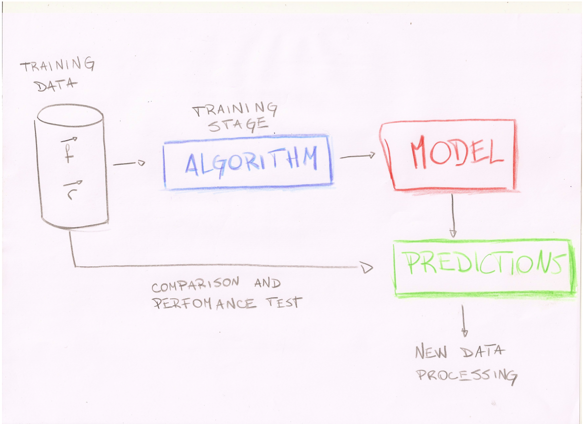
**Supervised learning**



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The machine learning jargon includes different terms:

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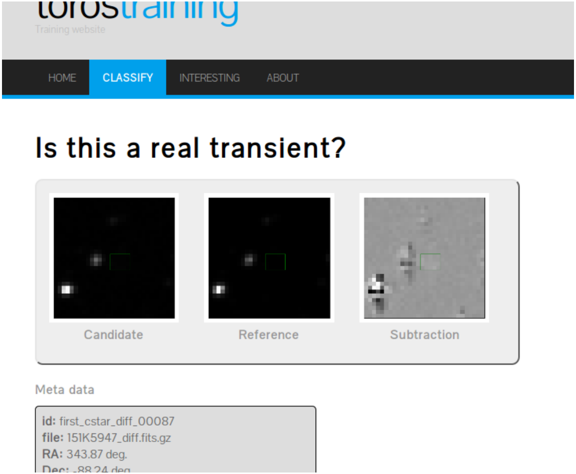
- **Features**: are the measurables that we can extract from a given instance. Also represented as a vector $\vec{f_i}$ for the instance number $i$. These features can be also categoric or numeric.
- **Labeled data**: these data are instances that we are going to use as training set. Labeled means that you already know which is the true class for each instance.

# Statistical Learning

So a dataset with a correct labeling of different objects is needed to obtain a classificator.
This can be achieved for example by using citizen science: `http://toros-dev.no-ip.org`



# Algorithms implemented

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- **Naive Bayes** Uses the Bayes's theorem in order to estimate probabilities of belonging to different classes.

$$P(c = R|\vec{f_i}) = \frac{P(\vec{f_i}|c = R)P(c = R)}{P(\vec{f_i})}$$

- **Logistic Regression**
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- **Naive Bayes**
- **Logistic Regression** This algorithm assumes that probabilities of belonging to a given class can be linearly interpolated after a simple transformation:

$$logi(p_R) = \ln(\frac{p_R}{1 - p_R}) = \alpha + \beta \times \vec{f_i}$$

- **Random Forest**

# Algorithms implemented

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- **Naive Bayes**
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- **Random Forest** This algorithm works growing decision trees by using two parameters: $N_{tree}$ the number of decision trees to be trained, and $N_f$ the number of random features on each tree. After training the decision is made taking into account all the trees votes.

# Constructing traning dataset

We simulated data giving a balanced set of 9202 *bogus* y 9120 *reals*.

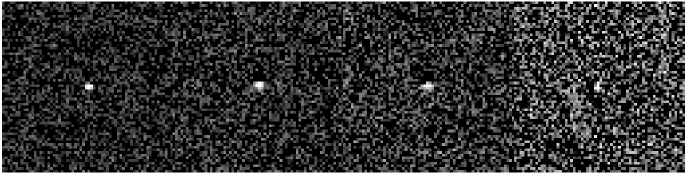

Figura: Stamps of bogus simulated objects.

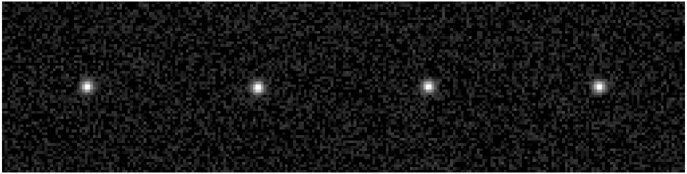

Figura: Simulated real objects.

# Procedure

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- PCA threw 310 principal components, giving also the transformation matrix, and features vectors already projected into the PCA space.
- The second method found that the best features were 39, and so we used this subsample to train the classificators.

# FOM

We call Figure of Merit to a set of estimators of a certain test perfomance. During every decistion process we deal with two possible errors:

| - | Desition | |
|---|---|---|
| Actual State | Reject $H_0$ | No reject $H_0$ |
| $H_0$ True | Type I Error | Correct |
| $H_0$ False | Correct | Type II Error |

This also represents the so called "Confusion Matrix"

# FOM

Some common quantities that measure the perfomance of a test are FDR, TPR, y FPR.

- FDR *False Discovery Rate* is the probability of making a Type I mistake, given that you already rejected $H_0$
- TPR *True Positive Rate*) is the probability of rejecting $H_0$ given that it is false, or 1- the probability of making a Type I mistake
- FPR (o *False Positive Rate*) is the probability of making a Type II mistake

# FOM

There is a compromise between FPR and TPR.
This compromise serves the preferences of the test's user for the confidence This curve is called *Receiver Operating Characteristic* or ROC.
The most used estimator is called AUC for *Area under the Curve*

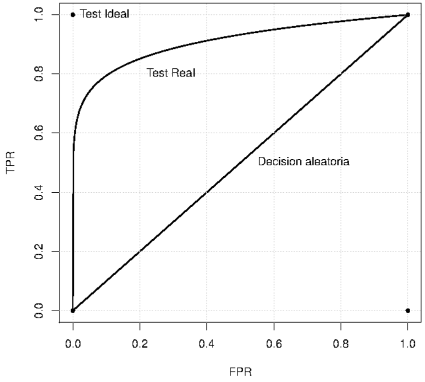



Figura: Curva ROC

# FOM

There are others FoM for different purpouses. FPR and TPR can be "fooled" in the presence of an unbalanced training set.
$N_B \sim \epsilon \times N_R$
In some data sets $\epsilon$ goes from 30 to 100. So the training set is unbalanced.

$$Precision = P(Y = 1|\hat{Y} = 1)$$
$$Recall = P(\hat{Y} = 1|Y = 1)$$
$$Specificity = P(\hat{Y} = 0|Y = 0)$$

Recall and Specificity relie on conditionals from the **true class labels**.
Precision relies on conditionals from **your estimate** of the true class label.

# FOM

**The Relationship Between Precision-Recall and ROC Curves**

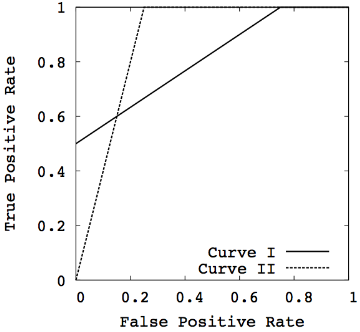



*Figure 11.* Comparing AUC-ROC for Two Algorithms

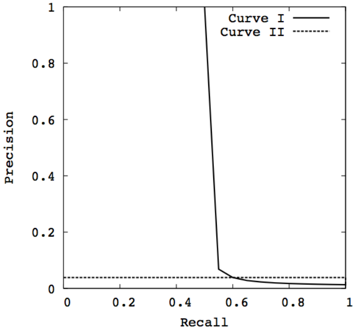
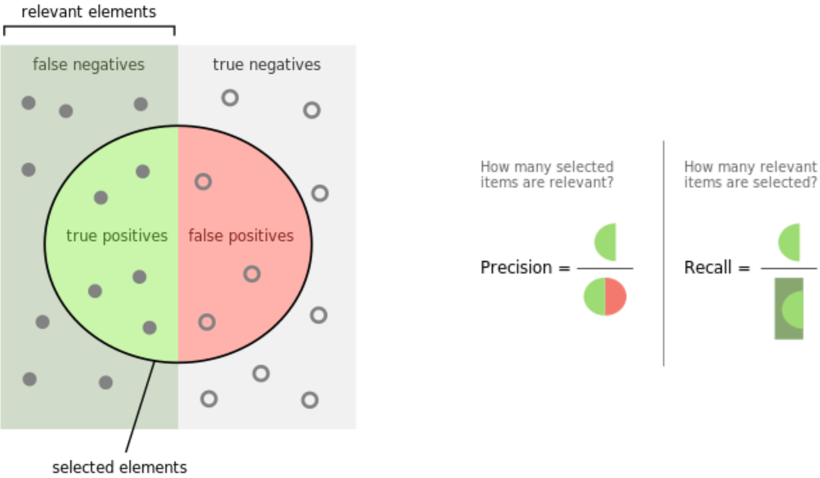


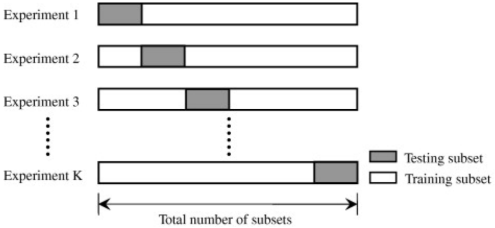

*Figure 12.* Comparing AUC-PR for Two Algorithms

# FOM


relevant elements
false negatives
true negatives
true positives
false positives
selected elements
How many selected items are relevant?
Precision =
How many relevant items are selected?
Recall =

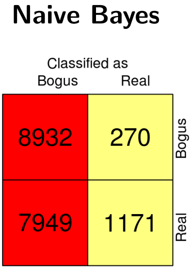
# K-fold cross validation

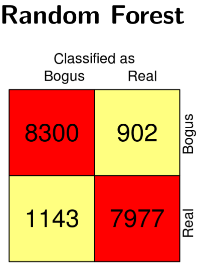
The perfomance was calculated using K-Fold Cross Validation algorithm, which divides the dataset into **K slices randomly sampled** and trains in K-1 folds while testing over the fold unused.

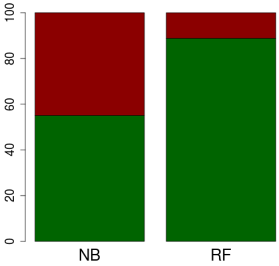



Since this can be performed K times, the testing gives K measures, and then those are combined to extract the TPR and FPR statistics.

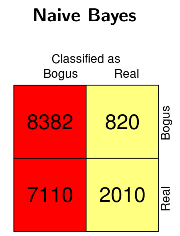
# Complete sample results

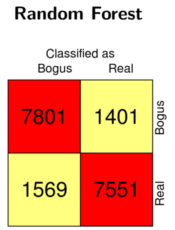


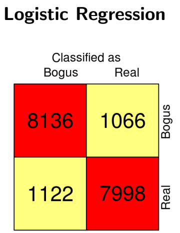



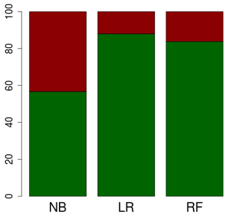



# PCA transformed sample results



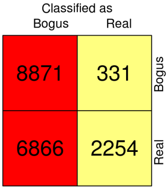



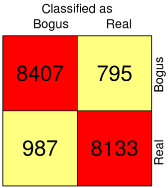



# Cfs selected features results

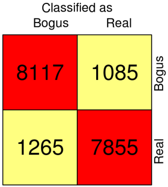
**Naive Bayes**

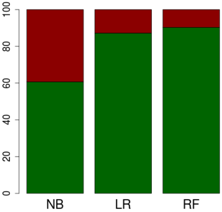



**Random Forest**




**Logistic Regression**



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- The results showed a powerful tool that can be employed easily and with high confidence.
- The flexibility of these methods make them exceptionally expandable to other situations.

# Future work

- Use this for TOROS/TORITOS (deployment on spring).
- Classify light curves

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**PREGUNTAS?? :D**