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Supervised WSD Using Master- Slave Voting Technique

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Abstract: *The Word sense disambiguation approaches contain number of methods such as stacking, voting, in this paper we combined three approaches, Decision List as Master approach and Naïve Bayes, Adaboost a Slaves approaches, for combining models to increase the accuracy and WSD performance.*
Keywords: *Decision List, Naïve Bayes, Adaboost, Senseval-3, WSD, WordNet, Master-Slave technique, Voting, combination.*

I. Introduction

Number of systems can be used for the ability of an algorithm to continue operating despite abnormalities in input, calculation etc, means it improves robustness. It there may be possibilities to create independent module for WSD, in that case we act each module individually for better performance. If there is combination of number WSD systems, the errors are find out and they are detected by a factor of 1/N. The main task of WSD is to assign sense to word in context. The senses of a word can be typically taken from dictionary. Various machine learning (ML) approaches are explained or evaluate to produce successful Word sense disambiguation systems [1]. But how the performance between different algorithms can measure still remains the question. Decision List and Naïve Bayes are used improve the performance. This performance is improved by collecting the voting. After collecting the voting accuracy of finding correct sense will get increased. Word Sense Disambiguation is open problem, so the output of any approach will depend on your particular data. Disambiguation means choosing one meaning from pre-specified set. The main idea is to determine similarity between every meaning and the context.

II. Master – Slave Technique

In WSD there are two main methods voting and stacking, the voting method can be weighted or non-weighted, the weighted approach done by adding more weight to the classifier which is selected by votes and got more accuracy among some classifiers. Here in the figure below show you our suggestion which called Master- Slave technique. In this model several classifier as slaves suns separately, and one or more can select by the Master. The selection depends on the accuracy, in case found two classifiers got same results, the master has control and decision to select according the reputation each one.

The Master-Slave technique [2] is a technique to achieve improvement in WEB Search engine results, by combination one or more of supervised classifiers, figure (1), shows the master-slave technique. In this experiment we combine two supervised classifier, Decision List as master approach [3], and Naïve Bayes, Adaboost as Slaves classifiers.

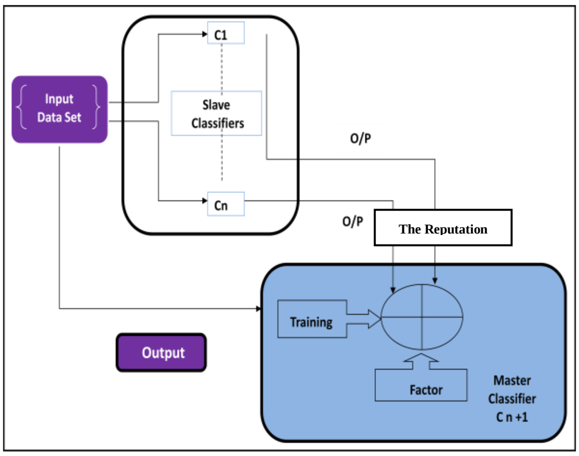

Figure 1: Mater – Slave technique

2.1 Decision List

A Decision List is an ordered list with conjunctive rule. It consists of sequence of tests, means for output result or finally obtained result the tests applied for each input. This type of iteration can be done until first test is applicable i.e. first test become classified as true or false, or negative or positive, assumes n Boolean attributes to be considered, we denote the set of such variables as:
Vn= {x1, x2, xn} [4]. Decision List was selected to be master approach in our model Master-slave technique.

2.2. Naïve Bayes

An advantage to use Naïve Bayes is that it requires data with, very small size to estimate the parameters necessary for classification. The technique is based on Bayesian theorem.

Given set of variable $\mathrm{P} = \{\mathrm{p1, p2, p \dots pd}\}$, we construct the probability for the event cj from the set of outcomes, $\mathrm{C} = \{\mathrm{c1, c2, c \dots cd}\}$. Her P is predictor and C is set of categorical levels, which act as dependent variable. Using Byes rule

$$\mathrm{X(cj|p1, p2, p \dots pd) \propto X(p1, p2 \dots pd|cj)p(cj)}$$

Where:

$$\mathrm{X(cj|p1, p2, p \dots pd) - posterior\ probility}$$

That means p belongs to cj. We can use Maximum A posteriori (MAP). Mainly is also known as decent classifier, so the probability outputs from predict- probability are not be taken too seriously.

Naïve Bayes, indicates as a strong independence assumptions between the features. Naïve Bayes requiring number of parameters, Bayes theorem is a technique for constructing classifiers. In that not a single algorithm is used, but a combination of algorithm which based on common principle. For example- a fruit may be considered to be orange, if it is orange, round and about 3 inch diameter, a naïve bayes classifier by considering each of these features [5].

2.3. Adaboost

In some case, the weak classifier need combine in such a way to improve the accuracy and create strong one. Ensemble method is an strategy to combine learning algorithms that have different methodology together. An application to WSD combination method is Adaboost, which is a general approach to create and contract a strong classifier from weak classifiers. The actual process carried out is as mentioned below (6).

Box (1): Adaboost Algorithm implemented

For x =1; x< m; x++)

Fetch weight αx from classifier cx

$$H(x) = sign\sum_{x=1}^{y} \alpha x(x(X))$$

}

Where H(x) sign is function for linear combine of weak learner to boost the performance.

To make learning process easier members of training data are weighted equally. Adaboost Algorithm treats it as an input. For X components, it is iterated y times one turn is allotted for each classifier. In case of master – slave technique the algorithms are selected on the basis of the accuracy which is decision List and the algorithms which is needs some boost in terms of accuracy are slaves, in this case Naïve bayes and Adaboost are acting as a slaves, in such way combining improve the accuracy of these slaves.

2.4. Ensemble Methods

For ensemble methods use more can one learning algorithm to obtain predictive performance as comparing constituent learning algorithms. Predictive performance means accuracy typically used in inductive learners. Robustness over single estimator the original ensembles method is Bayesian averaging [7].
Some method for constructing ensembles manipulates the example to finalize multiple hypotheses such as:

- Manipulate the set of input features.
- Manipulate the output, to obtain the good ensemble of classifiers for obtaining the values.

- Injecting randomness, used for generating ensembles of classifiers to inject randomness into the algorithm.

III. Experimental Setup

Experiments are conducted by using an approach to resolve word sense disambiguation. Input is nothing but 10 nouns and 5 verbs along with WordNet repository to know POS. Innovative approach which is based on Master-Slave model. Results are calculated on the basis of the said set up.

1. **Data Set:** five verbs and ten nouns are selected to perform the experiments of word sense disambiguation [8].
2. **Data Source:** WordNet 2.1[9] referred to several the details related with a particular word like part of speech (POS). This data source is used to resolve the disambiguation of various meanings related with given data set.
3. **Training Set:** To train the algorithm to identify correct sense of given word context is used. This context is in the form of snseval-3[10]. This means with reference of the context given with respective word. Training Phase plays important role in identification of correct meaning of a word from data set. Result of training phase is to make disambiguation task much easier.
4. **Testing Set:** Thus the calculated meaning of a word is verified in this testing phase.
5. **Algorithms:** Algorithms are written in java [11] which drives the meaning identification process. Master – Slave Voting Algorithm, this is an extension of algorithm process mentioned above where two algorithms or more are clubbed to deliver the maximum performance acting as a slave.
6. **Attributes:** Attributes is nothing but factors taken into the consideration for making the decision related with word sense disambiguation. There are various stages of this attribute, means while deciding the weight allotted for given meaning feature acts as attribute.

While dealing with Master-Slave model main task is to decide a particular algorithm as Master and other/ others as a Slave. So in this decision making process overall accuracy or F-measure of all algorithm acts as an attribute.

About topical and lexical context analysis, for example Suppose w-3, w-2, w-1, w, w+1, w+2, w+3 is the context of words before and after given word w (to solve word sense disambiguation). All information related with respective part of speech ($-3 \leq POS \leq 3$), and consider various combinations like (w-1, w+1), (w+1, w+2), (w,w+1,w+2), (w-1, w, w+1, w+2, w+3), these could be many more combinations of these words mentioned in a context. Together the set of all W, POS, is known as sample set for the attribute of given word environment [12].

7. **Combination algorithm applied:** the steps of combination algorithm we implemented as below**:**

- **Input –** data set of 15 words is used to disambiguation a word along with data source of WordNet and context.
- **Process-** java code is used to implement master- Slave model to improve the accuracy of an algorithm. Data processing, classification and accuracy calculation is carried out by this code.
- **Output-**Accuracy of this master- Slave model is decided by precision, recall and f-measure. Box1. Below shows the steps of combination algorithm implemented.

Box (2): Master-Slave combination Algorithm implemented steps

Step1. Accuracy of Master X % is collected.

Step2. Accuracy of Slave y %

Step3. Collect voting to improve X by using factor
F= (X - f)/100.

Step4. Accuracy of Word=old Accuracy + F

Step5. Apply this factor for all words, X1, X2,
X3…, and X15.

Step6. Calculate precision, Recall, and f-measure.

Master – Slave model deals with combination of algorithms to improve the result. This combination helps to increase the performance of an algorithm by boosting the accuracy of given algorithm. Algorithm is designed to implement Master-Slave technique to improve the performance of Naïve Bayes and Adaboost algorithms.

IV. Methodology

Master – Slave model deals with combination of algorithm to improve the result. This combination helps to increase the performance of an algorithm by boosting the accuracy of given algorithm.

To select Master and Slave experiment is conducted. After conducting the experiment and performing the necessary literature survey related with it following options or approaches are considered.

1. Select the Master, generally an algorithm with high accuracy, good history and utilization.
2. Combine existing algorithms to improvise the accuracy.
3. Variable Factor selection: The Master- Slave Architecture adds a factor to boost the performance of system if this factor is designed an fixed format, the value to be added will not be added differently for different words. How to treat a word with accuracy=100%.

In the factor that we add is decided $x - f/100$. Where x is the accuracy of an algorithm which is lagging and all the time we add $x - f/100$ to ensure addition in the accuracy. Hence all the time performance of the algorithm will get improved by referring Master- Slave model. This model is boosting the performance ensures the rise in the overall accuracy provided selection of adequate algorithm, with high accuracy should be made. Java code improved algorithm, which is written in Java [13], improves the accuracy by using delimiter function which is mention at step 2.3. This function will internally invoke several programs to conduct voting and find the correct sense.

V. The Experiments

5.1 First Experiment

The first combination deals with Naïve Bayes as classifier and Decision List as Master, experiment is conducted by considering decision list as a master and Naïve Bayes algorithm as a slave, after completing this experiment the accuracy of Naïve Bayes model (individual) got increased. To effect was possible only due to decision list (which is acting as a master).

Table 1: Data Set of Words and Results of Naïve Bayes and Decision list Combination

Word	POS	# Sense	First Combination Recall	First Combination Precision	First Combination F-Measure
Praise	**n**	**2**	**1000**	**500**	**1500**
Name	**n**	**6**	**1000**	**764**	**2292**
Worship	**v**	**3**	**1000**	**763**	**2289**
Worlds	**n**	**8**	**1000**	**702**	**2106**
Lord	**n**	**3**	**500**	**500**	**1500**
Owner	**n**	**2**	**500**	**500**	**1500**
Recompe-nse	**n**	**2**	**333**	**333**	**999**
Trust	**v**	**6**	**1000**	**143**	**429**
Guide	**v**	**5**	**1000**	**1000**	**3000**
Straight	**n**	**3**	**1000**	**1000**	**3000**
Path	**n**	**4**	**473**	**412**	**1236**
Anger	**n**	**3**	**922**	**500**	**1500**
Day	**n**	**10**	**250**	**250**	**750**
Favored	**v**	**4**	**167**	**167**	**501**
Help	**v**	**8**	**125**	**125**	**375**
			684.6667	**510.6**	**1531.8**

This table shows the F-measure which is calculated by knowing precision and recall with the help of following formula.

$$F - \text{measure} = \frac{2.\,\text{precision}.\,\text{recall}}{\text{precision} + \text{recall}}$$

Even after implementing Master-Slave model, the accuracy is not 100%.

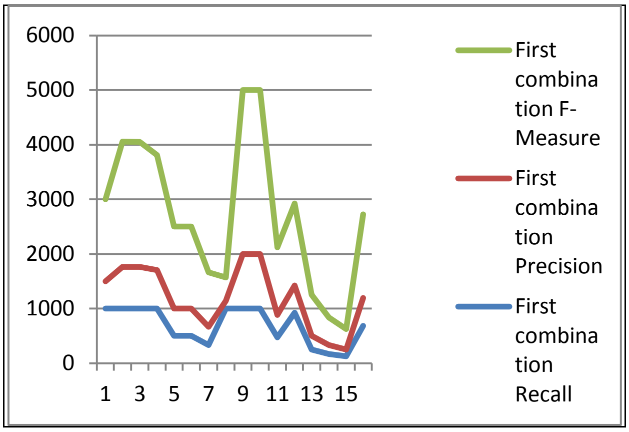

Fig.2. The first combinationGraph

When we look at the performance of the combination that we have selected, we can observe the considerable hike in the performance of Naïve Bayes algorithm.
This hike could be well interpreted by looking at the table of individual contribution of the Naïve Bayes algorithm [14].

5.2 Second Experiment

Experiment conducted accuracy is increased, this combination experiment deals with Adaboost as slave classifier, to improve the accuracy more and more. Experiment is conducted and it is observed that this combination gives better result.

Table 2: Data Set of Words and Results of Adaboosts and Decision list Combination

Word	POS	# Sense	Second Combination		
			Recall	Precision	F-Measure
Praise	**n**	**2**	899	1000	3000
Name	**n**	**6**	1000	1000	3000
Worship	**v**	**3**	996	1000	3000
Worlds	**n**	**8**	141	1000	3000
Lord	**n**	**3**	465	1000	3000
Owner	**n**	**2**	942	1000	3000
Recompe-nse	**n**	**2**	963	1000	3000
Trust	**v**	**6**	167	167	501
Guide	**v**	**5**	500	510	1530
Straight	**n**	**3**	500	500	1500
Path	**n**	**4**	333	333	999
Anger	**n**	**3**	500	500	1500
Day	**n**	**10**	111	1000	3000
Favored	**v**	**4**	250	250	750
Help	**v**	**8**	125	125	375
			526.1333	692.3333	2077

This table shows the F-measure which is calculated by knowing precision and recall, and below the results graph of the combination between Adaboost and decision list.

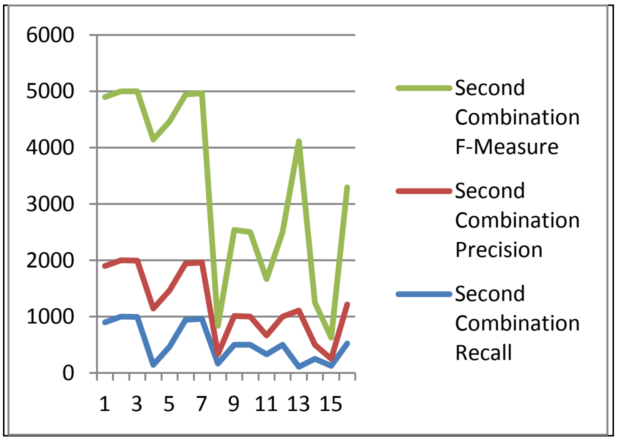

Fig.3. The second combinationGraph

5.3 Third Experiment

Now after two experiments above, we combined the three approaches Naïve Bayes and Adaboost as slaves with master approach which is Decision list, and as per the anticipation highest accuracy is received.

Table 3: Data Set of Words and Results of Naïve Bayes, Adaboosts and Decision list Combination

Word	POS	# Sense	Third Combination		
			Recall	Precision	F-Measure
Praise	**n**	**2**	**771**	**1000**	**3000**
Name	**n**	**6**	**1000**	**1000**	**3000**
Worship	**v**	**3**	**494**	**676**	**2028**
Worlds	**n**	**8**	**142**	**1000**	**3000**
Lord	**n**	**3**	**483**	**1000**	**3000**
Owner	**n**	**2**	**848**	**1000**	**3000**
Recompe-nse	**n**	**2**	**882**	**1000**	**3000**
Trust	**v**	**6**	**167**	**167**	**501**
Guide	**v**	**5**	**500**	**971**	**2913**
Straight	**n**	**3**	**500**	**500**	**1500**
Path	**n**	**4**	**333**	**333**	**999**
anger	**n**	**3**	**500**	**500**	**1500**
Day	**n**	**10**	**111**	**1000**	**3000**
Favored	**v**	**4**	**250**	**250**	**750**
Help	**v**	**8**	**125**	**125**	**375**
			473.7333	**701.4667**	**2104.4**

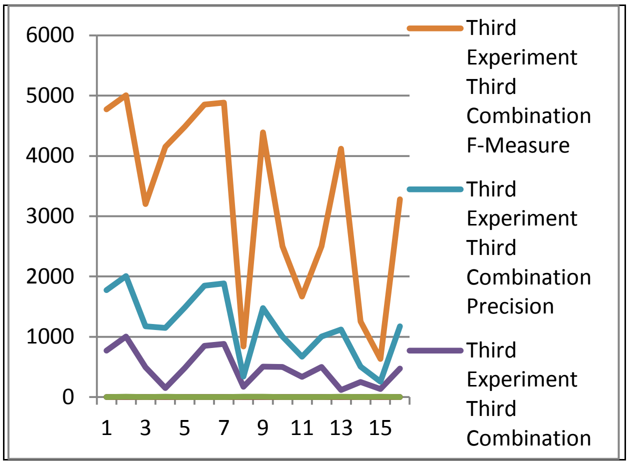

Fig.4. The third combination Graph

VI. Comparison Approaches of Master – Slave model combination

By looking to the graphs (2, 3, 4), and make Comparative analysis of three experiments of Master-Slave model to observe rise in the performance of Naïve Bayes algorithm. So this model gives hike in the individual performance of second and third combination experiments. The graph below

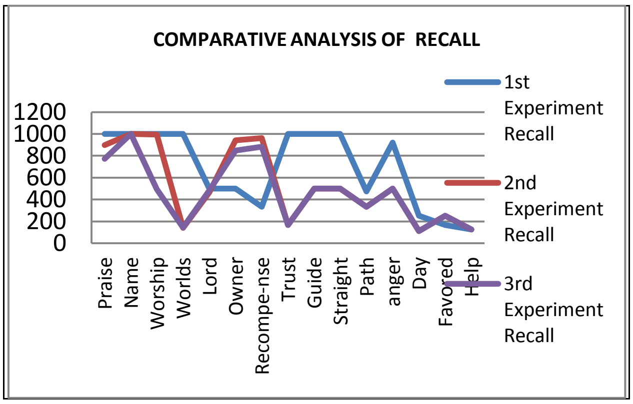

Fig. 5 Master-Slave thechinue

The Comperative Combination Recall Graph

And table (7) at end of paper shows the comparative results of Master- Slave technique.

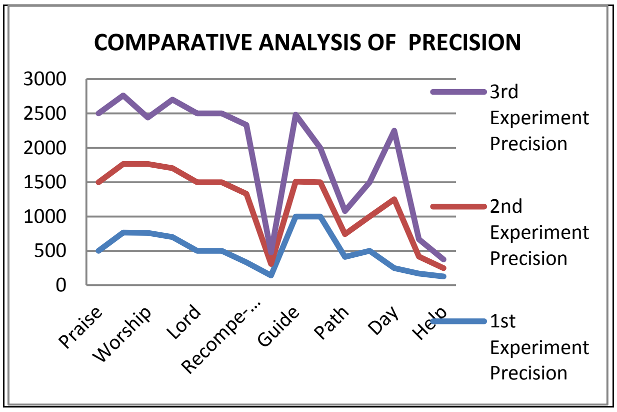

Fig.6. The Comperative Combination precision Graph

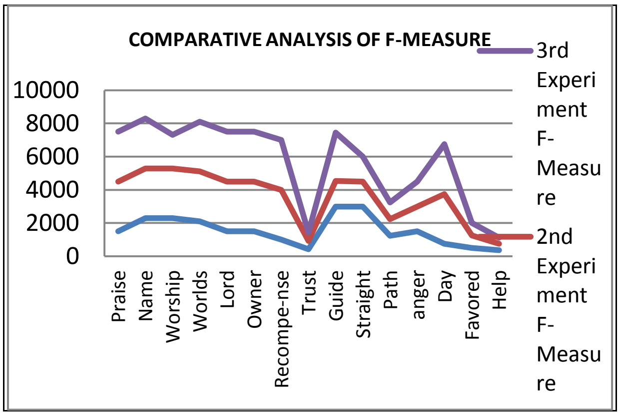

Fig.7. The Comperative Combination f-measure Graph

VII. Conclusion

In this paper, we presented Master- Slave technique suggested, in the first experiment, Decision list acts a Master and Naïve Bayes act as slave. Individually each algorithm gives good values of precision and f-measure. When they are combined together recall is enhanced which might be useful application like search engine which requires more coverage of sample space, but word sense disambiguation it is less useful.

In the second experiment, we Decision list as a master and Adaboost as a slave. There is increase in precision by (1.0733) and f-measure (3.2). Unlike to the first experiment recall is decreased. This is enhancement in precision to resolve word sense disambiguation problem.

In the third experiment combination, the decision list as master, call the Naïve Bayes and Adaboost together. It is observed that there in increases in precision and f-measure by (48.7367) And (146.2) respectively, this combination gives all round performance for precision.

At final the Master – Slave technique worked well to increase the performance of Slave algorithms by boosting the accuracy of the algorithms. Type of Slave, context will play very crucial role in the growth of f-measure. These experiments motivate to consider number of Slaves and type of Slaves carefully to make the disambiguation process more and more accuracy. Since the emphasis is more on precision and f-measure effort are not highlighted in the values of recall.

Table 4: The Results of three approaches before combination

No.	Approach	Before Combination		
		Recall	Precision	F- measure
1	N.Bayes	**305.73**	**628.6**	**1885.8**
2	D. List	**440.33**	**691.26**	**2073.8**
3	Adaboost	**459.2**	**652.73**	**1958.2**

Table 5: The Results of three approaches after combination

Approach	After Combination		
	Recall	Precision	F- measure
1st Experiment (N.Bayes + D.L)	684.6667	510.6	1531.8
2nd Experiment (D.L+ Ada)	526.1333	692.3333	2077
3rd Experiment (N.Bayes + Ada +D.L)	473.7333	701.4667	2104.4

The table below shows the final improvement on supervised approaches we implemented.

Table 6: The enhancement combination achieved

Approach	Enhancement		
	Recall	Precision	F- measure
1st Experiment (N.Bayes + D.L)	378.9367	-118	-354
2nd Experiment (D.L+ Ada)	85.8033	1.0733	3.2
3rd Experiment (N.Bayes + Ada +D.L)	14.5333	48.7367	146.2

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Table 7: The final Comparative Result of Master- Slave Technique

Word	POS	# Sense	First Combination			Second Combination			Third Combination		
			Recall	Precision	F-Measure	Recall	Precision	F-Measure	Recall	Precision	F-Measure
Praise	**n**	**2**	**1000**	**500**	**1500**	**899**	**1000**	**3000**	**771**	**1000**	**3000**
Name	**n**	**6**	**1000**	**764**	**2292**	**1000**	**1000**	**3000**	**1000**	**1000**	**3000**
Worship	**v**	**3**	**1000**	**763**	**2289**	**996**	**1000**	**3000**	**494**	**676**	**2028**
Worlds	**n**	**8**	**1000**	**702**	**2106**	**141**	**1000**	**3000**	**142**	**1000**	**3000**
Lord	**n**	**3**	**500**	**500**	**1500**	**465**	**1000**	**3000**	**483**	**1000**	**3000**

Owner	**n**	**2**	**500**	**500**	**1500**	**942**	**1000**	**3000**	**848**	**1000**	**3000**
Recompe -nse	**n**	**2**	**333**	**333**	**999**	**963**	**1000**	**3000**	**882**	**1000**	**3000**
Trust	**v**	**6**	**1000**	**143**	**429**	**167**	**167**	**501**	**167**	**167**	**501**
Guide	**v**	**5**	**1000**	**1000**	**3000**	**500**	**510**	**1530**	**500**	**971**	**2913**
Straight	**n**	**3**	**1000**	**1000**	**3000**	**500**	**500**	**1500**	**500**	**500**	**1500**
Path	**n**	**4**	**473**	**412**	**1236**	**333**	**333**	**999**	**333**	**333**	**999**
anger	**n**	**3**	**922**	**500**	**1500**	**500**	**500**	**1500**	**500**	**500**	**1500**
Day	**n**	**10**	**250**	**250**	**750**	**111**	**1000**	**3000**	**111**	**1000**	**3000**
Favored	**v**	**4**	**167**	**167**	**501**	**250**	**250**	**750**	**250**	**250**	**750**
Help	**v**	**8**	**125**	**125**	**375**	**125**	**125**	**375**	**125**	**125**	**375**
			473.733 3	**701.466 7**	**2104.4**	**526.133 3**	**692.333 3**	**2077**	**473.733 3**	**701.466 7**	**2104.4**