In your words, and in no longer than 2 pages, Summarize the paper thoroughly heightening the subject of research, the major contributions, the conclusions, and your own commentary.

Hopfield associative memory can store n-tuples of +1's. This associated memory relates to the network. At any instant, the state of the neural network is a collective state of individual neurons.
The associative structure is based upon the neural net. The state of neurons represent one bit of information and the state of the system as a whole is described by a binary n-tuple. Every neuron contributes to the sum of binary states of neurons in the system.

This paper applies the techniques from the coding theory rigorously to study the maximum capacity in Hopfield associative memory. Hamming distance is used between two states in binary n-space under consideration. It seems like anything under n/2 can serve purpose in many situations. The n-tuple input, which is less than n/2 hamming distance from the fundamental memory is transformed into the memory (entailing its recovery) by transforming the connections in the network into the sum of outer products of the memories, and this may have implementation limitations.

The paper defines that If *m* basic memories are picked at random and most original memories can be recovered exactly, the maximum value of fundamental memories that could be stored is n/(2log n). However, if restriction is added such that each one of the *m* fundamental
memories be recovered exactly, then the maximum capacity of the network is n/(4log n), as *n* approaches infinity. Extensions of the capacity under quantization of the external connection matrix are also considered. The question of the presence of extraneous memories with references to some current findings is also discussed.

Two modes of changing are discussed in this paper x→x'. There are two operations - Synchronous in which each of the n neurons simultaneously evaluates and updates its state according to following rule and Asynchronous operation, the components of the current state vector x are updated one at a time according to following rule.

$$x_i' = \operatorname{sgn}\left\{ \sum_{j=1}^{n} T_{ij} x_j \right\} = \begin{cases} +1, & \text{if } \Sigma T_{ij} x_j \geq 0 \\ -1, & \text{if } \Sigma T_{ij} x_j < 0 \end{cases}.$$

Where T_{ij} is the synaptic weight matrix and x = ($x_1, x_2 \ldots\ldots, x_n$) is the present state of the system with $x_j = \pm 1$, state of j*th* neuron. x_i is the new state that is determined by the rule described above.

The non-symmetrical connection matrix T is an issue not included in this paper. These occur in real neural networks, of course. For arbitrary matrices our case for energy minimisation in the next section fails. In addition, fixed points do not even need to exist and different forms of orbital behavior may take place..

High degree of parallelism, distributed storage of information, robustness, and very simple basic elements performing tasks of low computational complexity are included to recapitulate.
Vectors x are required which are memories in the state space of the neural network be fixed points of the system.

The foundation of the paper lies on the paper by JJ Hopfield in 1982- "Neural networks and physical systems with emergent collective computational abilities". Hopfield has shown that we always hit a fixed point in the asynchronous model for all T symmetric relation matrix, starting anywhere. Here is a region of attraction around the fundamental memories in both the asynchronous and synchronous cases. Since some error-correcting or "pull-in" capability is required, "forced model" is assumed in this paper, i.e if few components are not known, they are guessed and are right half of the. So, if exactly 20% of the n memory components is known, and estimate is the other 80% with error-probability of ½, this is like knowing 20 percent + (l/2) X 80% = 60 percent correctly.

For the asynchronous case, there are three convergence choices at least, two of which are discussed in the paper. Firstly, radius *pn* can be drawn directly or monotonously to its central memory, so that each transformation in a variable is actually a shift is in the right direction. The synchronous version always goes in one step to its fundamental memory center. Secondly, a random step is in the right direction with sufficient probability but not likelihood 1. After enough steps, the test will have very close relationships with its fundamental memory center, so that we are directly attracted by all subsequent changes in the right direction. This means two-iteration convergence in the synchronous case.

The paper is based on the fact that for any fundamental memory, there is a domain or basin of attraction, with high likelihood one comprising an almost n/2, or almost a majority sphere of radius. This means that the majority of the probe vectors in some positive range on Hamming spheres around most basic memories, in both the asynchronous and synchronous models, should hit the fundamental memory at the center of the sphere as a stable or fixed point if there are not too many basic memories from the very beginning. If so many fundamental memories remain, they are not even fixed points

In this paper there are two distinct cases. First, each of the m fundamental recollections can be fixed with high probability and nearly the complete ρ*n*-sphere is attracted. Second, and this concept is weaker and almost every memory is, as above, highly probable, good but not every memory necessarily good. It turns out that this decrease essentially doubles its capacity.

Finally, the paper summarizes four expressions based on different scenarios for the capacity of the Hopfield length *n* memory when a random, independent probability is seen with 1/2 fundamental memories to store and check with a probe of n-tuple at maximum *pn* distance away from a fundamental memory ($0 \leq \rho < 1/2$).

(i) If the unique fundamental remembrance must be recovered with high probability, except for a disappearing small fraction of the basic memories through direct convergence into the fundamental memory, then the maximum capacity comes out to be-

$$\frac{(1-2\rho)^2}{2}\frac{n}{\log n}$$

(ii) In the above scenario, if there is no exception fundamental memory, then maximum capacity is:

$$\frac{(1-2\rho)^2}{4}\frac{n}{\log n}$$

(iii) If $0 \leq \rho < ½$, if some wrongs are permitted, and a small fraction of exceptional fundamental memories is allowed, then:

$$\frac{n}{2\log n}$$

(iv) If the scenario is same as above i.e. some wrong moves are permitted, (although two synchronous moves suffice), but no fundamental memory is exceptional

$$\frac{n}{4\log n}$$

To conclude, this paper has successfully accomplished the task of deriving the expressions, however, the extraneous fixed points are mentioned not to be fundamental memories. But very few of the original *m* memories are fixed exactly. In fact, the linear capacity leads to the only fixed points which are indeed extraneous at and near the limits of the radius ρn spheres around the fundamental memories. Also, no clear idea is provided about the appearance of the extraneous points. In addition, T_{ij} is approximately gaussian and pairwise independent. This does not seem to be sufficient to strictly cover the case with the asymptotic result mentioned above. The difficulty is to consider, at once, the growing number of T_{ij}.