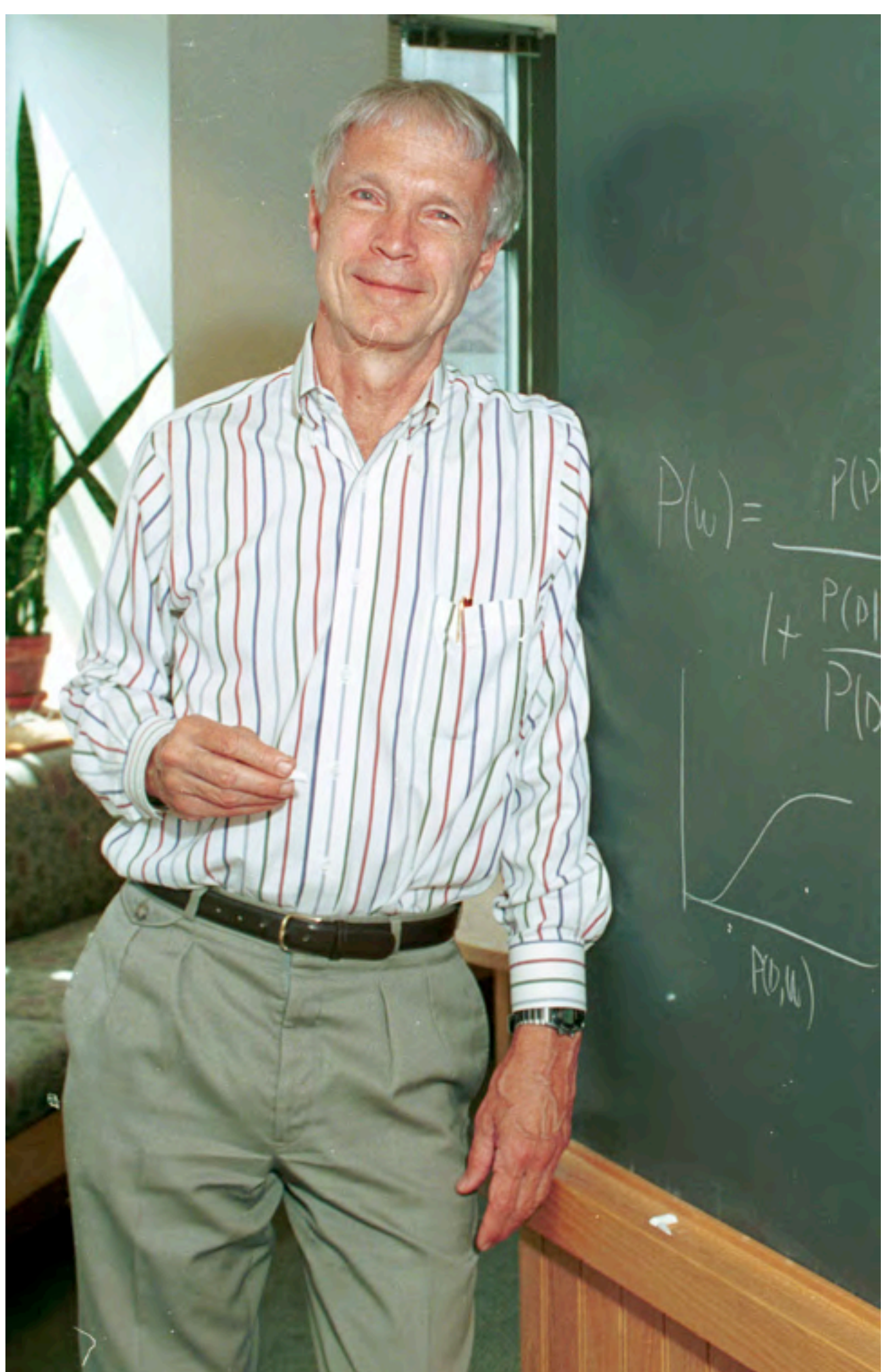


# John J. Hopfield

What is physics? To me—growing up with a father and mother both of whom were physicists—physics was not subject matter. The atom, the troposphere, the nucleus, a piece of glass, the washing machine, my bicycle, the phonograph, a magnet—these were all incidentally the subject matter. ... Physics was a point of view that the world around us is, with effort, ingenuity, and adequate resources, understandable in a predictive and reasonably quantitative fashion. Being a physicist is a dedication to a quest for this kind of understanding.

Text: APS News, Aug/Sep 2007.

Photo: Princeton University Office of Communications



As with many of the people we honor at these events, John has been honored before, has served our community, ...



and used to be a  
bit younger.\*



\*Photo from the Emilio Segrè Visual Archives @ AIP.  
Keywords: Middle age | three-quarter view | Suits (clothing) ...



Perhaps less obviously, he enjoys  
the open ocean,



and is remarkably comfortable  
in a tuxedo.

# Chapter I: Solid state physics.

PHYSICAL REVIEW

VOLUME 112, NUMBER 5

DECEMBER 1, 1958

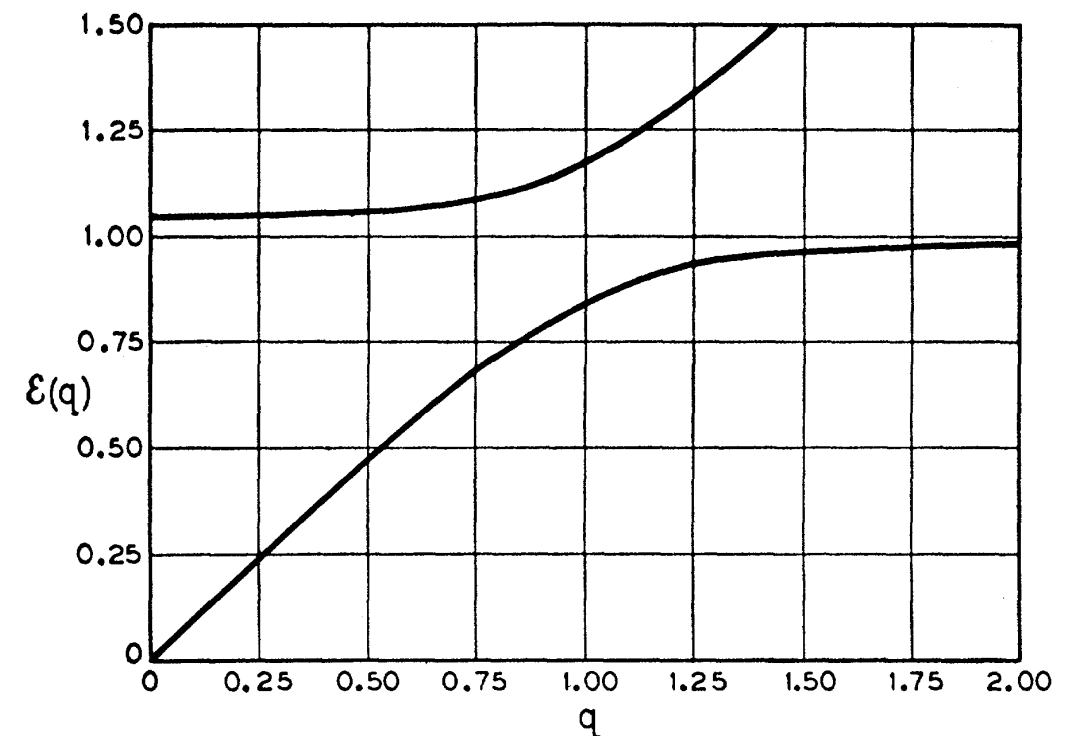
## Theory of the Contribution of Excitons to the Complex Dielectric Constant of Crystals\*†

J. J. HOPFIELD†

*Physics Department, Cornell University, Ithaca, New York*

(Received July 16, 1958)

The operators  $a_{k\lambda}^*$  are exactly the photon creation operators of the usual Maxwell field while the  $b_{k\lambda}^*$  are creation operators for the polarization field. The polarization field “particles” analogous to photons will be called “polaritons.”



Thank you, Al. I have done my best to repay you through similarly nurturing another generation of independent students. (JJH, 2014)

# Theoretical and Experimental Effects of Spatial Dispersion on the Optical Properties of Crystals

J. J. HOPFIELD\*†

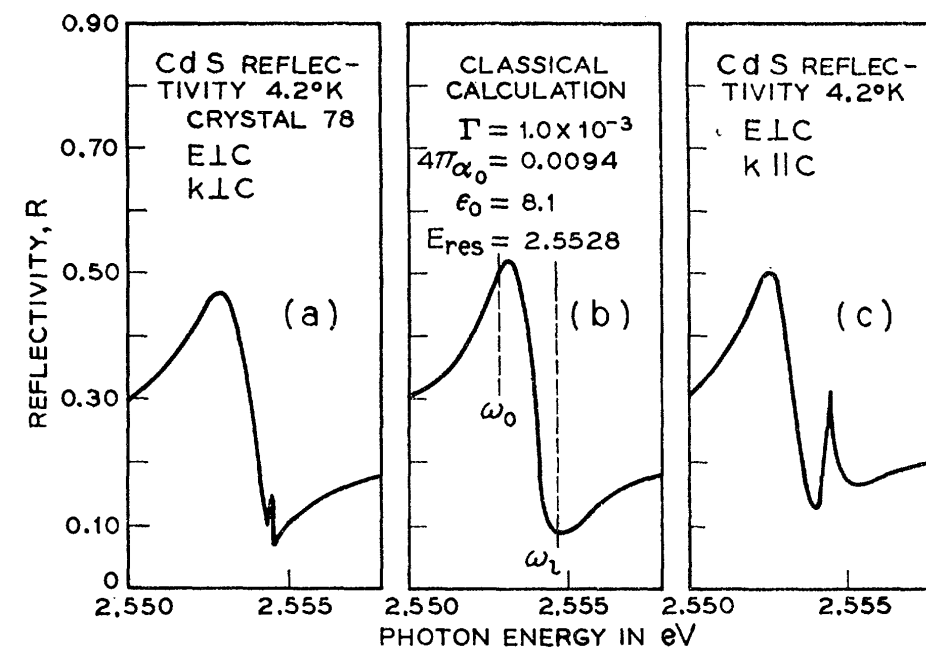
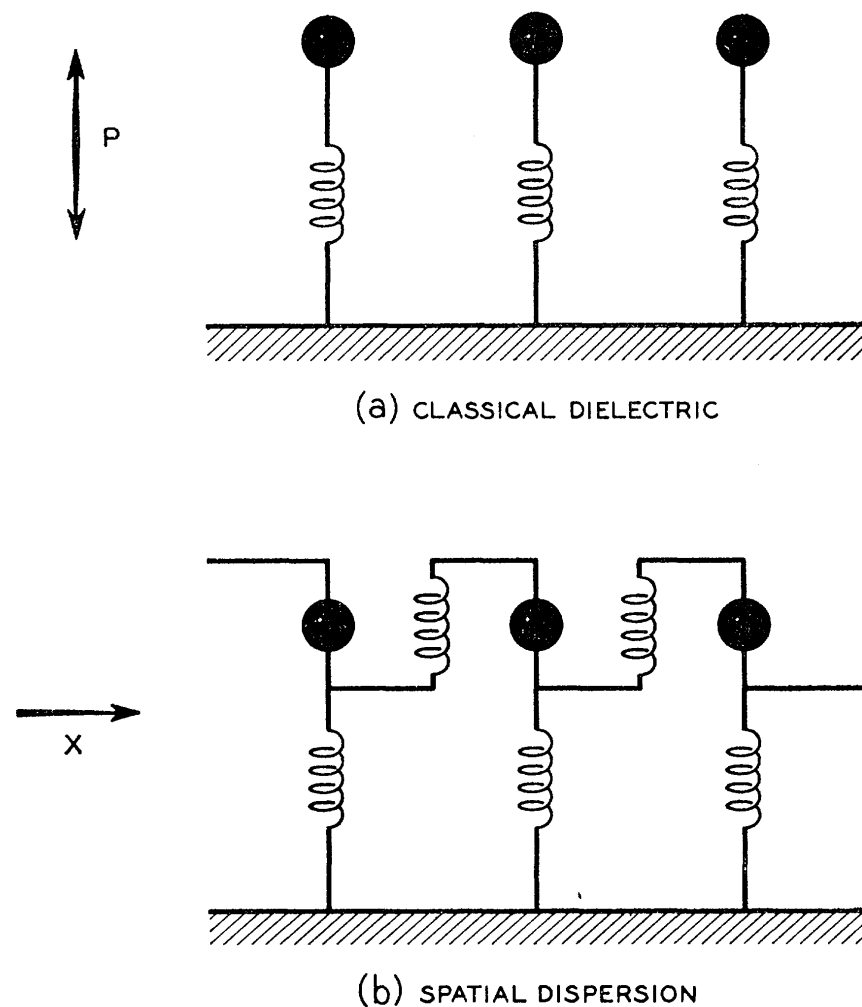
*Department of Physics, University of California, Berkeley, California*

AND

D. G. THOMAS

*Bell Telephone Laboratories, Murray Hill, New Jersey*

(Received 14 June 1963)

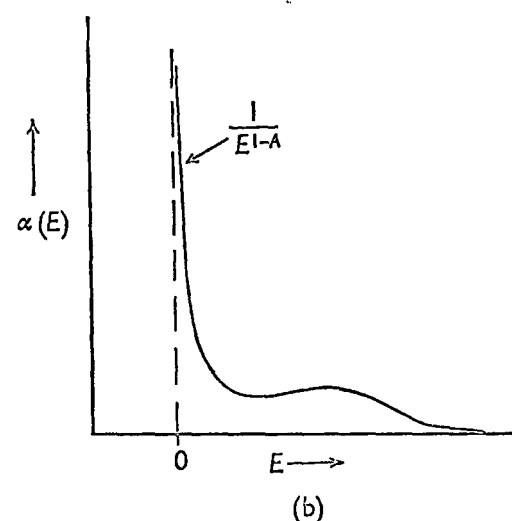
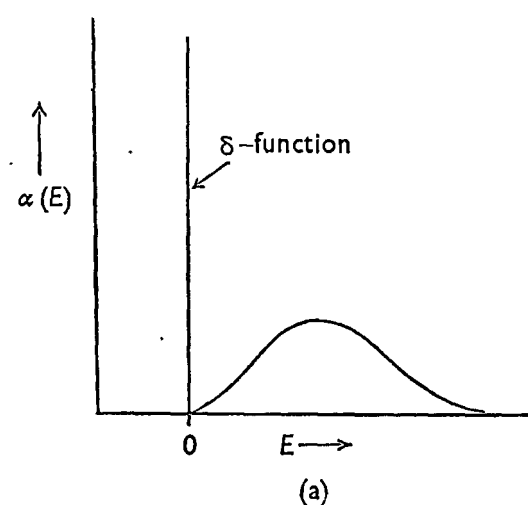


... a paper that had a picture of balls coupled by springs ... Balls and springs were pretty much the only thing he understood until he went horribly non-linear with neural networks.

Steve Girvin (2014)

## Infrared Divergences, X-Ray Edges, and all that

This spectrum is the calculated shape of an x-ray transition between two levels on an atom placed in a Fermi sea of infinite extent. Whereas one might have expected a  $\delta$ -function line plus an electronic excitation wing, there is no  $\delta$ -function component, but only a one-sided wing as in Fig. 1(b). The absence of a  $\delta$ -function part is due to the orthogonality of the Fermi-sea ground state with  $V(r)$  to the initial ground state (the “orthogonality catastrophe”).



[A personal historical note. I ran into the orthogonality problem through questions of zero-bias anomalies in tunnelling. The basic argument of Hall *et al.*<sup>8</sup> on zero-bias anomalies was incorrect, but could have been correct if the electron-phonon coupling ( $\bar{n}$ ) had been infinite. A search (much later) for possible infinite coupling constants turned up the Fermi gas “orthogonality catastrophe”. When an attempted application of this to tunnelling proved uninteresting the subject was dropped.]

This Comment on the nature of the theory would not be complete without noting one last reason for theoretical interest in this problem; namely, that the Kondo problem of a magnetic impurity in a Fermi gas can be related to an *iterated* x-ray problem.

His behind the scenes role in some other developments should get mention. He was there and involved in the whole story of the x-ray anomaly, the Kondo solution etc.. He assigned Mahan the problem in the first place, he was in Cambridge with me when Yuval and I solved it, but somehow his name never appeared on the papers.

# Chapter II: Foundations for a theoretical physics of biological systems

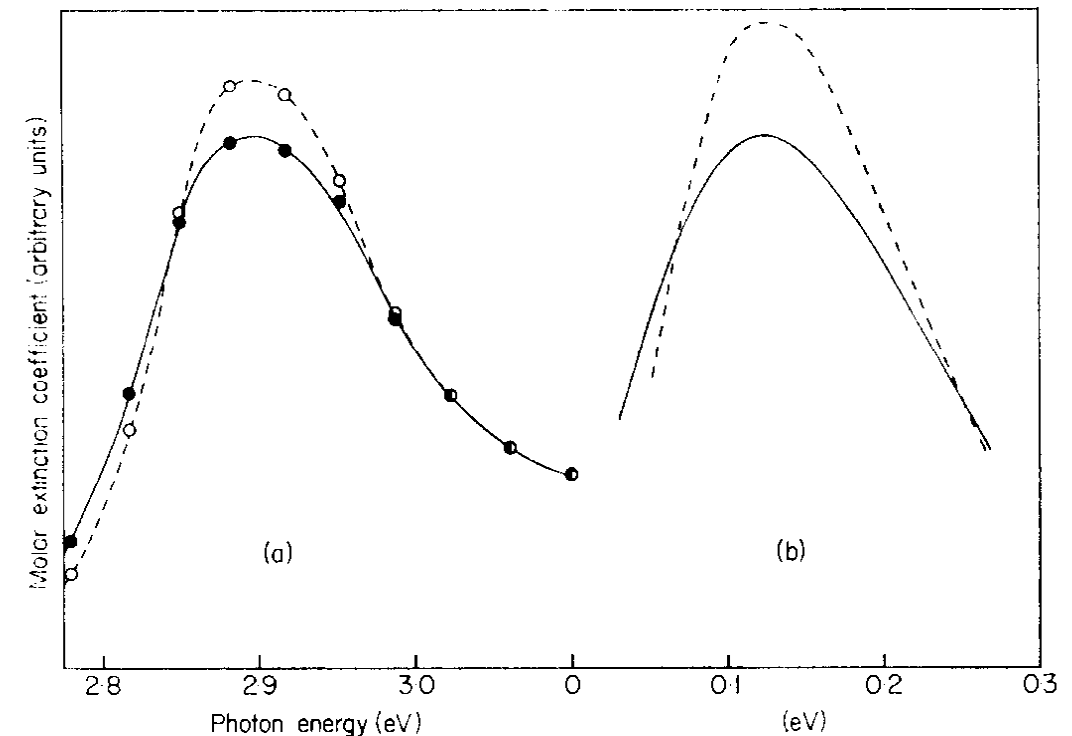
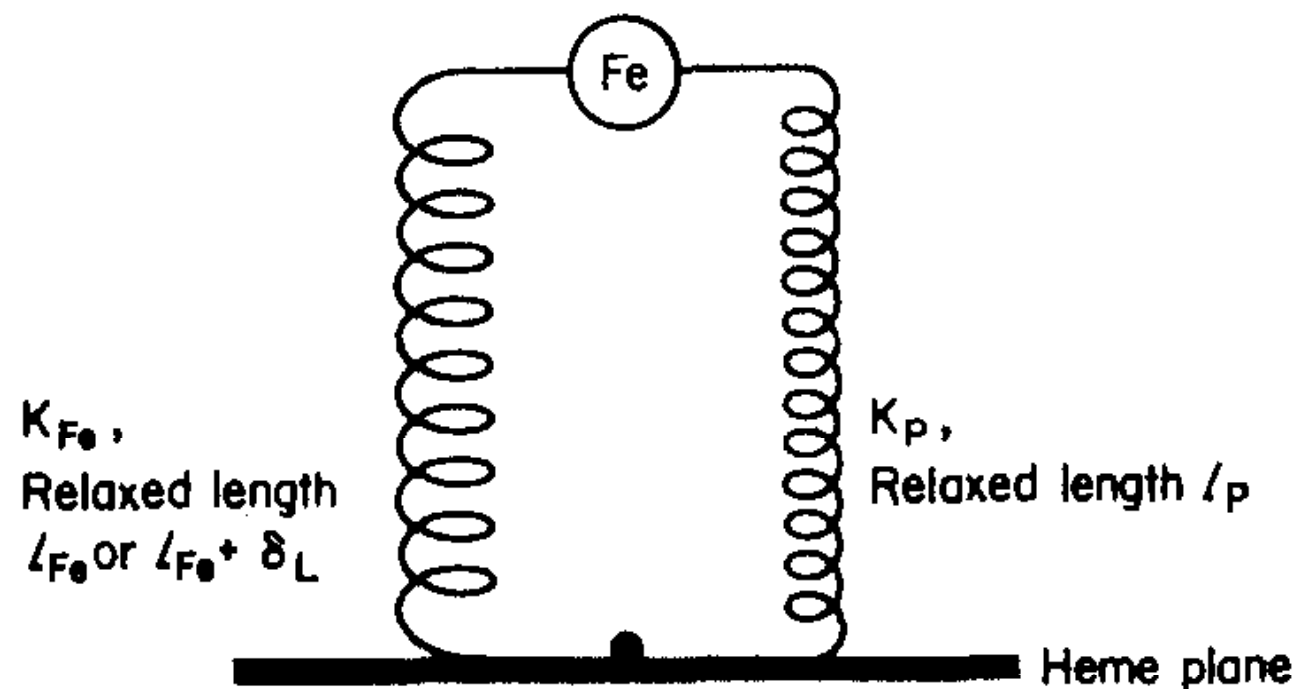
*J. Mol. Biol.* (1973) **77**, 207–222

## Relation between Structure, Co-operativity and Spectra in a Model of Hemoglobin Action

J. J. HOPFIELD

*Department of Physics, Princeton University  
Princeton, N.J. 08540, U.S.A.*

*(Received 11 December 1972)*



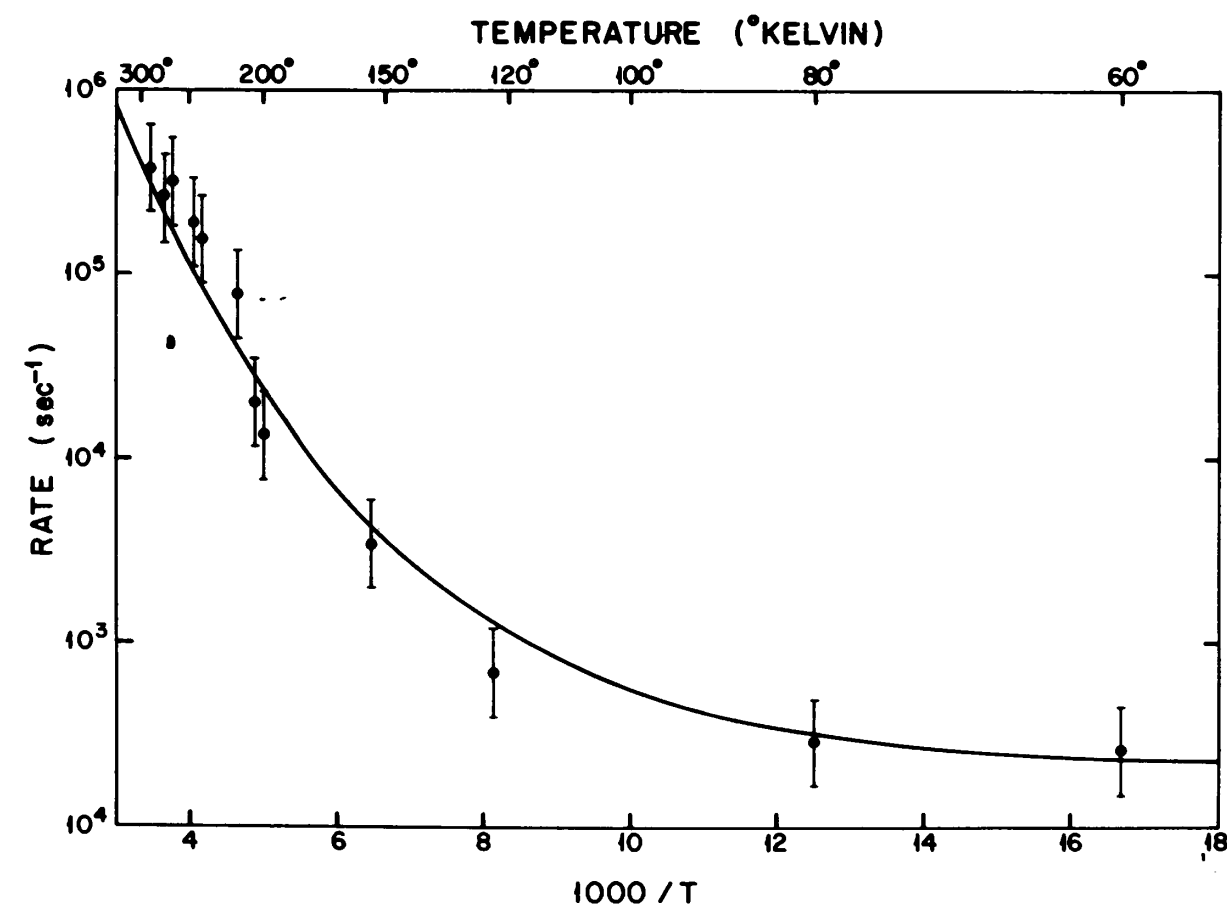
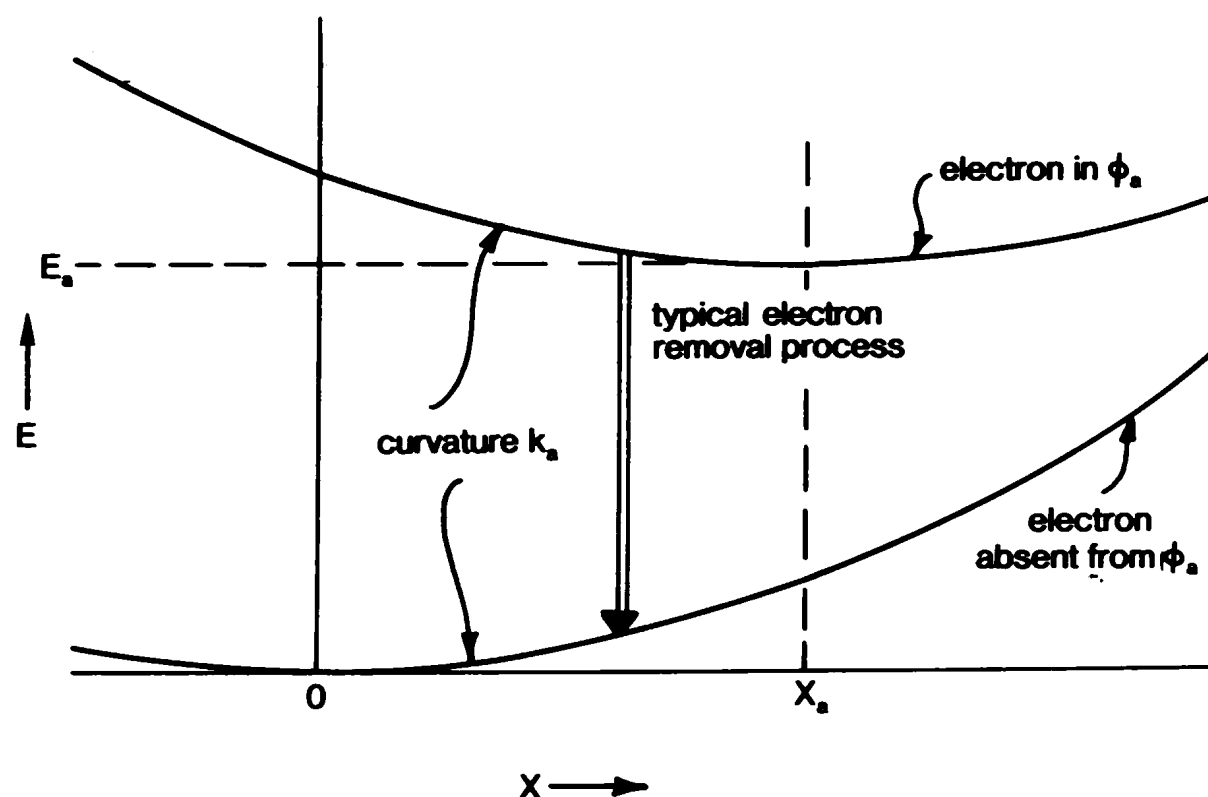
# Electron Transfer Between Biological Molecules by Thermally Activated Tunneling

(photosynthesis/oxidative phosphorylation/cytochromes)

J. J. HOPFIELD

Department of Physics, Princeton University, Princeton, New Jersey 08540; and Bell Laboratories, Murray Hill, New Jersey 07974

*Contributed by J. J. Hopfield, June 24, 1974*





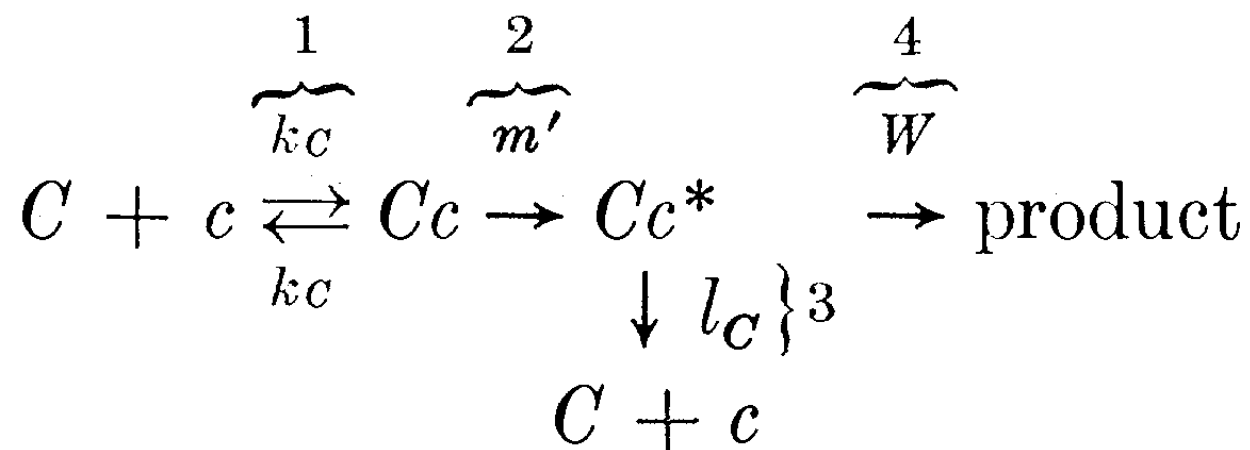
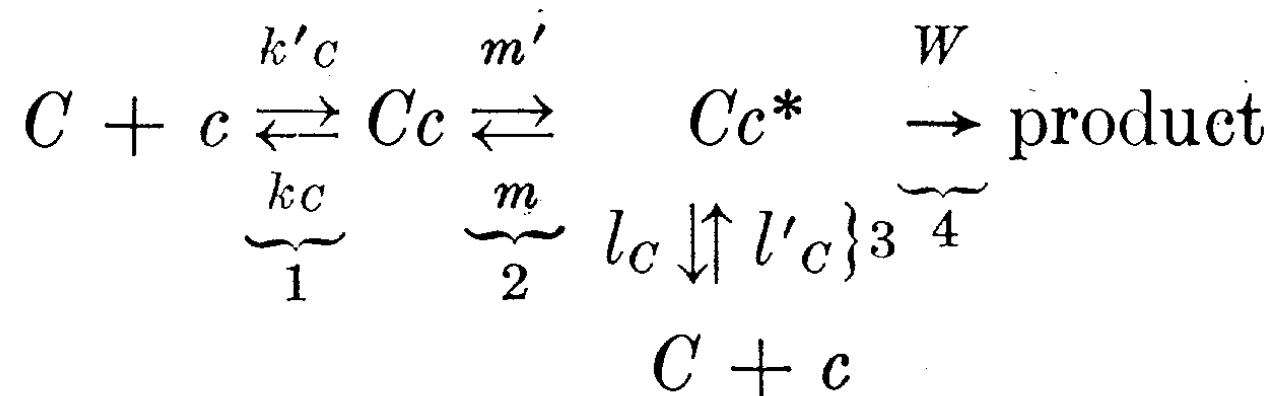
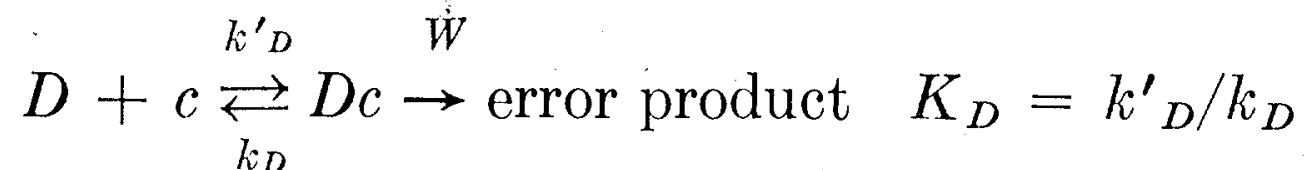
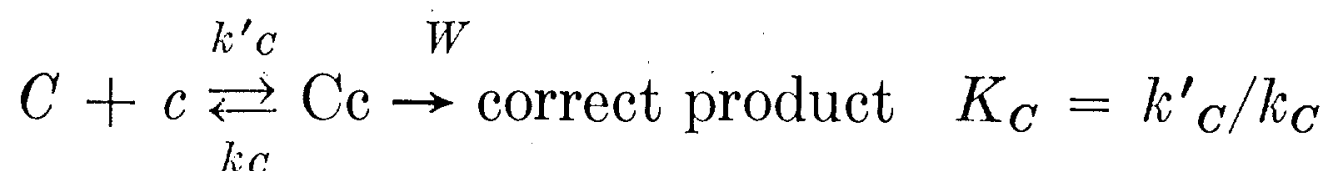
# Kinetic Proofreading: A New Mechanism for Reducing Errors in Biosynthetic Processes Requiring High Specificity

(protein synthesis/DNA replication/amino-acid recognition)

J. J. HOPFIELD

Department of Physics, Princeton University, Princeton, New Jersey 08540; and Bell Laboratories, Murray Hill, New Jersey 07974

Contributed by John J. Hopfield, August 6, 1974



Something to note about these three papers

*(Received 11 December 1972)*

*Contributed by J. J. Hopfield, June 24, 1974*

*Contributed by John J. Hopfield, August 6, 1974*

# Chapter III: Thinking about the brain

*Proc. Natl. Acad. Sci. USA*  
Vol. 79, pp. 2554–2558, April 1982  
Biophysics

## Neural networks and physical systems with emergent collective computational abilities

(associative memory/parallel processing/categorization/content-addressable memory/fail-soft devices)

J. J. HOPFIELD

Division of Chemistry and Biology, California Institute of Technology, Pasadena, California 91125; and Bell Laboratories, Murray Hill, New Jersey 07974

*Contributed by John J. Hopfield, January 15, 1982*

$$\begin{array}{l} V_i \rightarrow 1 \\ V_i \rightarrow 0 \end{array} \quad \text{if} \quad \begin{array}{l} \sum_{j \neq i} T_{ij} V_j > U_i \\ \sum_{j \neq i} T_{ij} V_j < U_i \end{array}$$

Suppose we wish to store the set of states  $V^s$ ,  $s = 1 \cdots n$ . We use the storage prescription (15, 16)

$$T_{ij} = \sum_s (2V_i^s - 1)(2V_j^s - 1) \quad [2]$$

The model has stable limit points. Consider the special case  $T_{ij} = T_{ji}$ , and define

$$E = -\frac{1}{2} \sum_{i \neq j} \sum T_{ij} V_i V_j \quad [7]$$

# Olfactory computation and object perception

(neural network/learning/sensory systems)

J. J. HOPFIELD

Divisions of Chemistry and Biology, California Institute of Technology, Pasadena, CA 91125

*Contributed by J. J. Hopfield, April 11, 1991*

Consider the case of two odors and two processing cells. The scale of the odor vectors is arbitrary, as is the scale of the functions  $a_k(t)$ . Each odor vector  $S_1$  and  $S_2$  has two components, one of which can in each case be picked as “1” to define the arbitrary scale. The two odor vectors can therefore be taken to be

$$S_1 = \begin{pmatrix} 1 \\ a \end{pmatrix} \quad S_2 = \begin{pmatrix} b \\ 1 \end{pmatrix} \quad [2]$$

Odor 1 thus excites processing cell 2 with strength  $a$  relative to its excitation of cell 1. The components  $a$  and  $b$  will be assumed to be positive, although this is not essential. From Eq. 1

$$I_1(t) = a_1(t) + a_2(t)b \quad I_2(t) = a_1(t)a + a_2(t). \quad [3]$$

At any single time  $t$ , the measurement of  $I(t)$  yields two equations in four unknowns—namely,  $a_1(t)$ ,  $a_2(t)$ ,  $a$ , and  $b$ . They cannot be determined from two equations. Adding more sampling times does not help, for each new sampling time  $t'$  introduces two more equations and two more unknowns,  $a_1(t')$  and  $a_2(t')$ . The problem is unsolvable in the general case.

There are, fortunately, a variety of circumstances under which the functions  $a_k(t)$  are less than completely general and which lead to an ability to solve for all the desired information. The simplest of these is the case in which the fluctuations with time of one odor are not correlated with the fluctuations of the other odor.



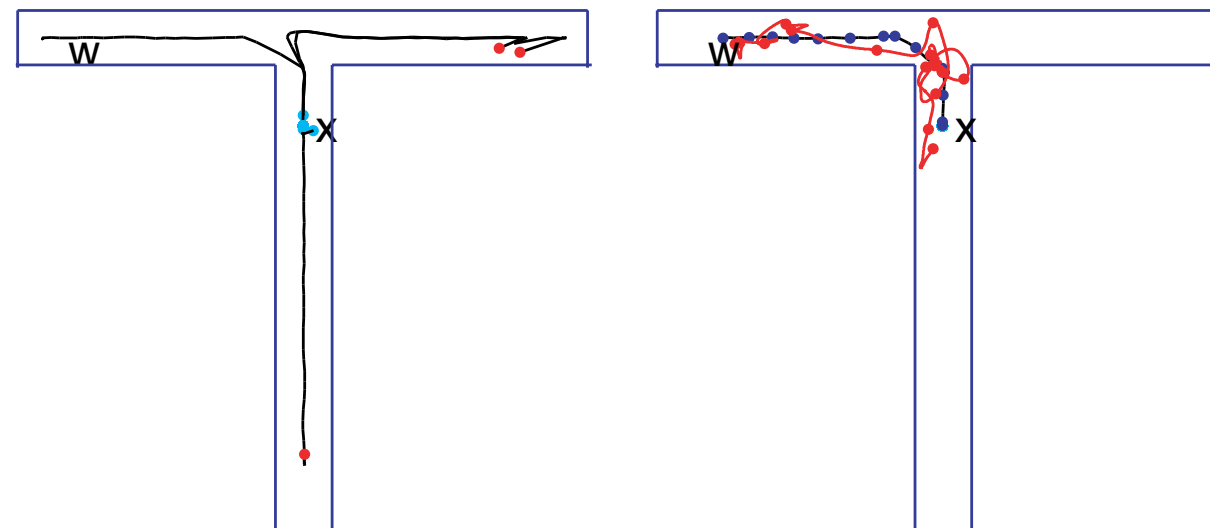
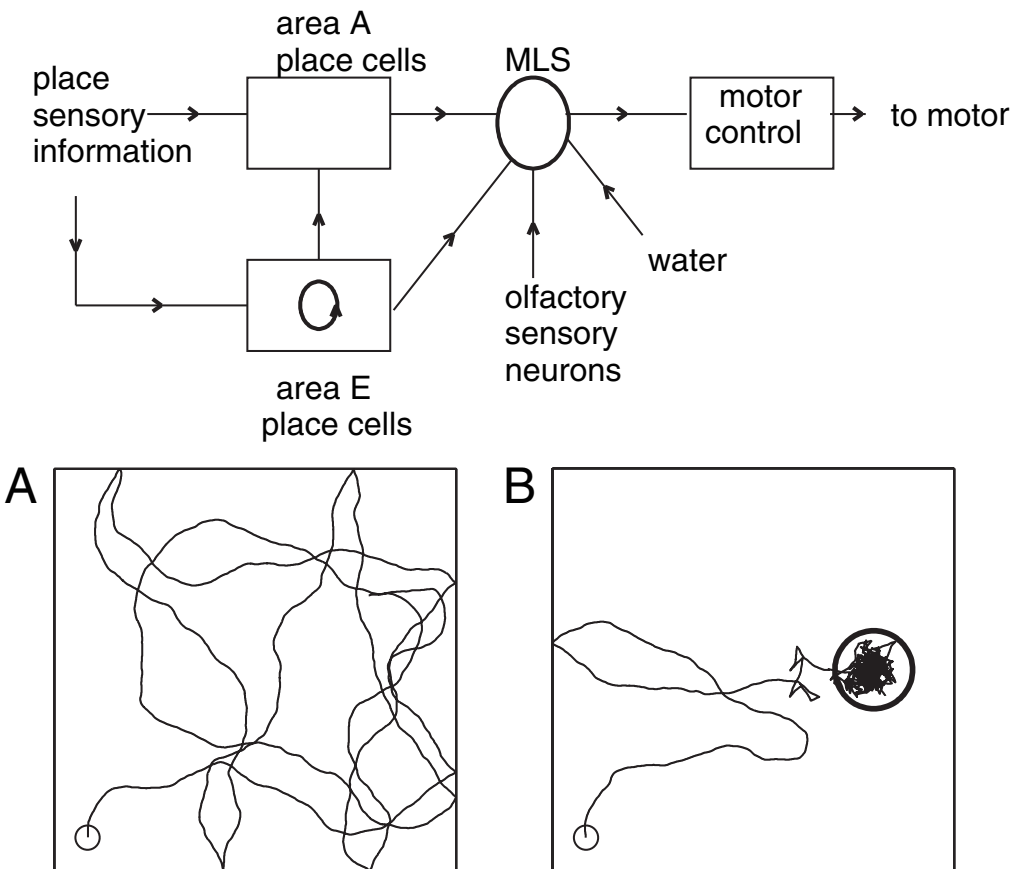
# Neurodynamics of mental exploration

John J. Hopfield

Neuroscience Institute, Carl Icahn Laboratory, Princeton University, Princeton, NJ 08544

Contributed by J. J. Hopfield, December 4, 2009 (sent for review October 15, 2009)

Three key ideas are embedded in the modeling. First, in circumstances for which a network of simple neurons has activity dynamics characterized by an attractor surface, adapting can produce a continuing exploration on that surface. Second, when an activity trajectory has been experienced that achieves a desired “mental” goal, synaptic learning produces an ability to mentally repeat that intended trajectory. Third, this repetition controls the motor system in such a fashion that the physical path taken corresponds to the path described by the trajectory of mental activity. The modeling is loosely based on some of the most salient facts about the rodent hippocampus.



There is, of course, much more.

A few words from friends.

John, in his own words:  
**Annu Rev Cond Matt Phys 5, 1-13 (2014).**

# Chapter IV