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Data-driven predictive maintenance and time-series applications

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Data-driven Predictive Maintenance and Time-Series Applications

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Υπάρχει στον κόσμο τούτον ένας μυστικός νόμος – αν δεν υπήρχε, ο κόσμος θα 'ταν από χιλιάδες χρόνια χαμένος – σκληρός κι απαραβίαστος: το κακό πάντα στην αρχή θριαμβεύει και πάντα στο τέλος νικάται.

–Νίκος Καζαντζάκης, Ελευθερία ή Θάνατος

There is a secret law in this world - if it didn't exist, the world would have been lost thousands of years ago - hard and inviolable: evil always prevails in the beginning and is always defeated in the end.

–Nikos Kazantzakis, Freedom or Death

Στην οικογένειά μου

To my family

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