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It is certified that the above statement made by the student is correct to the best of my/our knowledge.

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## **List of Abbreviations**

IM Influence Maximization

IC Independent Cascade

LT Linear Threshold

**NOMC** Number of Maximal Cliques

**SOC** Size of Clique

**CIM** Clique based Influence Maximization

**EWS** Edge Weight Sum

FIC Finding Initial Communities

**FC** Final Communities

**DSC** Dice Similarity Coefficient

SN Seed node

**DIC** Detecting initial communities

MSC Merging small communities

SIM Similarity based Influence Maximization

**CSC** cut similarity community

**PCI** Power community Index