

References*

David Meyer

dmm@1-4-5.net

Last update: October 26, 2018

1 Introduction

This document contains references for the machine learning and networking parts of Project Number HE201707000. These references, in non-alphabetical order, are: [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51]. Note that these references do not in general contain introductory references such as [52].

*This document is the final deliverable for Project Number HE2017070001.

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