Module 5.8 : Line Search

Just one last thing before we move on to some other algorithms ...

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def do_line_search_gradient_descent():
    w, b, etas = init_w, init_b, [0.1, 0.5, 1.0, 5.0, 10.0]
    for i in range(max_epochs):
        dw, db = 0, 0
        for x,y in zip(X, Y):
            dw += grad_w(w, b, x, y)
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        min_error = 10000 #some large value
        best_w, best_b = w, b
        for eta in etas:
            tmp_w = w - eta * dw
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- We will come back to this when we talk about second order optimization methods

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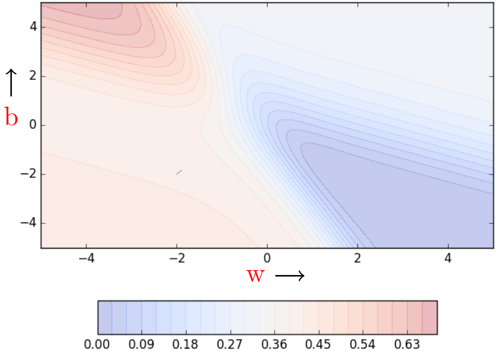

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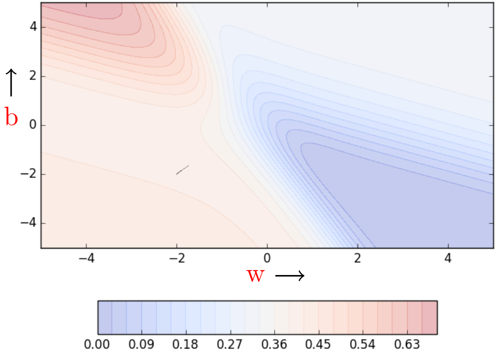

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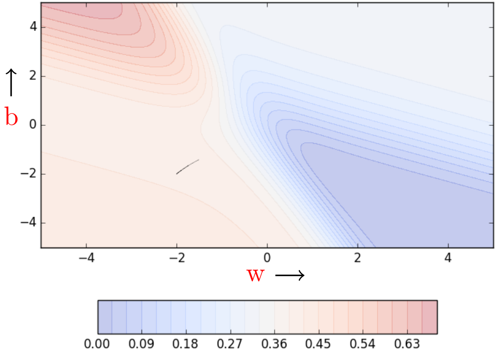

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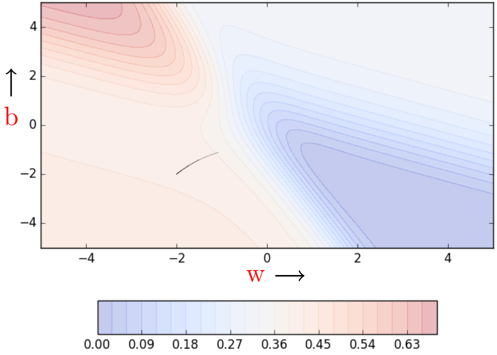

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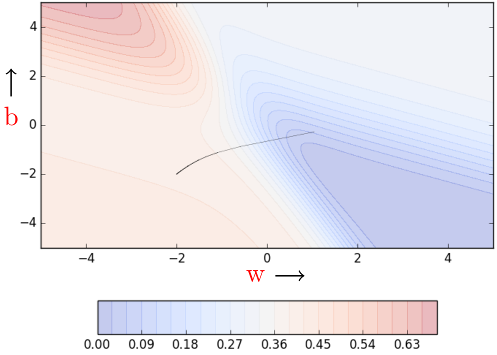

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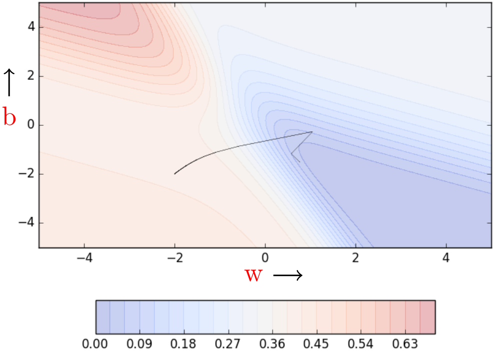

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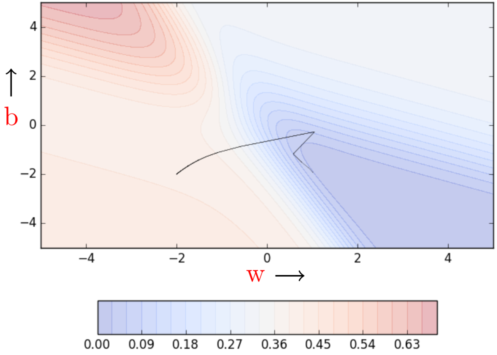

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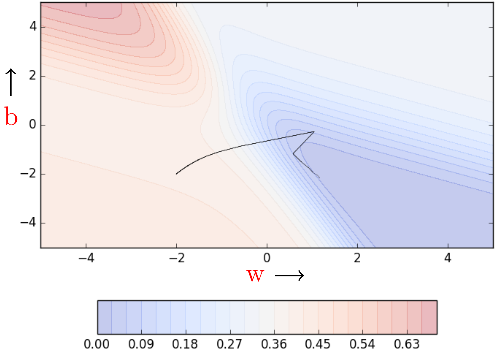

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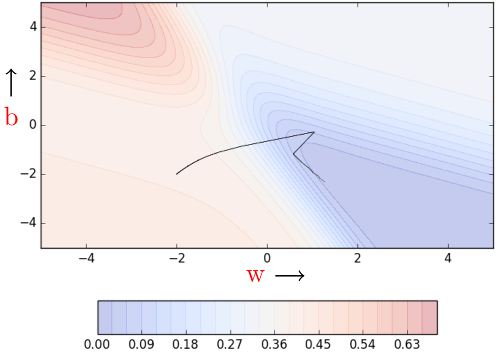

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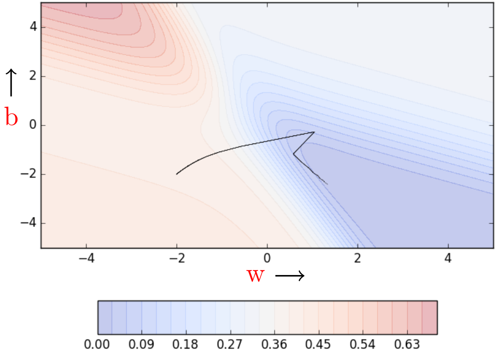

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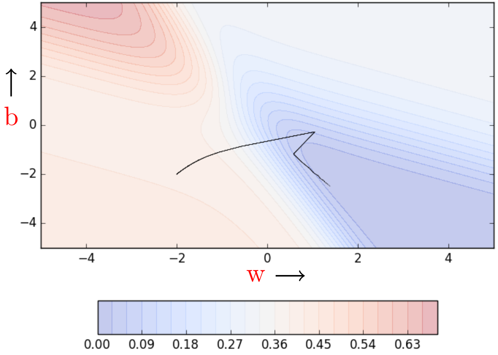

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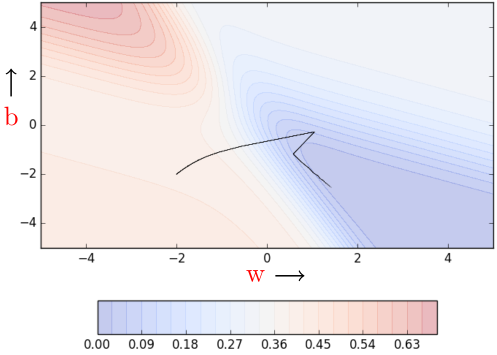

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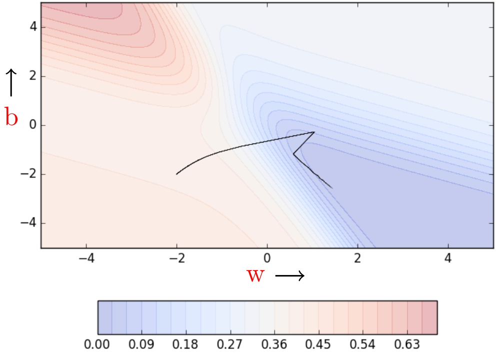

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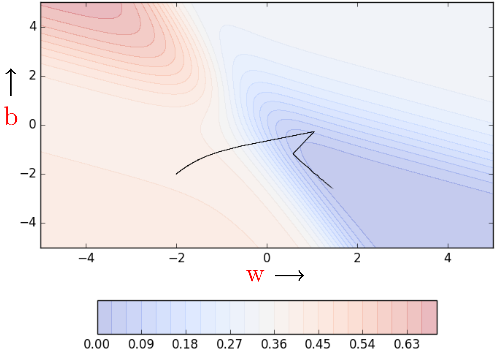

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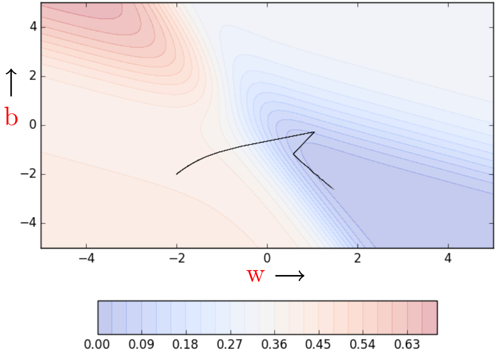

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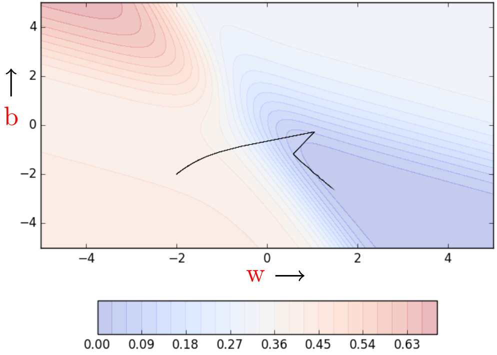

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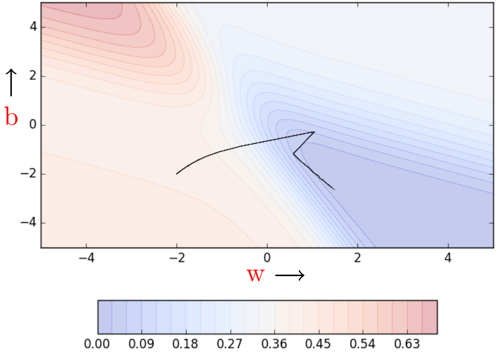

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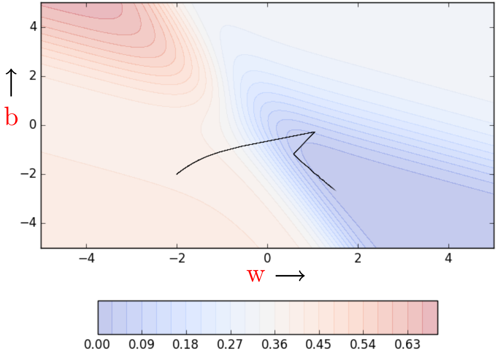

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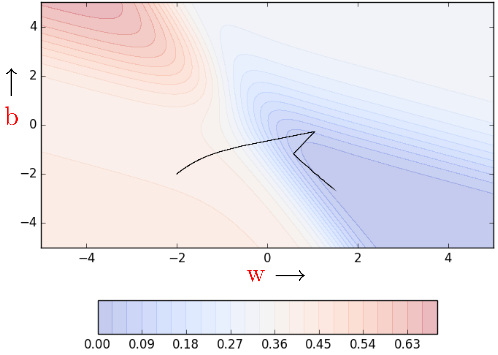

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